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

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Abstract

We develop a task-based framework of wage determination where a mismatch between the tasks performed as part of current and previous employment leads to persistent salary penalties. We exploit novel worker-level and longitudinal job task information from a labor market where task mismatch is endemic—the US biomedical PhD labor market—finding that task mismatch explains between-sector heterogeneity in the pecuniary returns to postdoctoral training: a positive postdoc salary premium emerges when task mismatch is low and a negative premium when it is high. Differences in accumulated task-specific human capital explain the sizably negative returns to postdoctoral training in industry. (*JEL* J24, I26, J31, J44)

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1 Introduction

Creative fields such as entertainment, the arts, entrepreneurship, and science are highly competitive, attracting many young workers of whom only a small share establish successful careers. Aspiring professionals in creative fields typically face substantial uncertainty—in their ability, talent, the quality of their ideas, or their preferences—that is often resolved only after an extensive period of specialized training (i.e., investment in *task-specific* human capital).[1] The non-routine and differentiated nature of the job tasks that attract young workers to creative fields also subject these workers to a substantial risk of task mismatch occurring when the tasks performed as part of specialized training differ from those performed in future ("plan B") employment. Prior research finds that workers experience persistent salary penalties due to task mismatch, that the cost of task mismatch is highest among college-educated workers (Gathmann and Schönberg, 2010; Guvenen et al., 2020), and that the returns associated with analytical skills are particularly pronounced (Stinebrickner, Stinebrickner, and Sullivan, 2019; Lise and Postel-Vinay, 2020).

While high-skilled workers face the greatest salary penalties from a given degree of task mismatch, they are less likely to switch occupations than other workers and tend to experience lesser degrees of task mismatch when they do (Gathmann and Schönberg, 2010). In this paper, we identify a natural environment where a sizable share of high-skilled workers regularly experience large, abrupt dislocations between job tasks and task-specific analytical skills—the US biomedical PhD labor market[2]—finding that task mismatch explains between-sector heterogeneity in the pecuniary returns to education of a given type—postdoctoral training in biomedicine—which range from significantly positive to significantly negative, and that differences in task-specific human capital are important to explaining the sizable lifetime earnings disparities between postdoc-trained and nonpostdoc-trained biomedical doctorates in industry.

This paper joins a rapidly growing literature in labor economics that treats skill as multidimensional, jobs as sets of tasks to be performed ("task requirements"), and the accumulation of human capital as task-specific.[3] Our paper is one of few in the task-specific human capital literature able

[1]An aspiring opera singer may spend years in voice training before discovering she does not have the talent to make a career of it. Failure rates among entrepreneurs are notoriously high, with would-be entrepreneurs investing time and money into the wide-range of skills needed to develop an idea into business, identify specialized talent to hire as employees, and operate the business. The young scientist spends years training to become a tenure-track researcher, often finding out near the end of that training their true aptitude as an academic researcher.

[2]The following statement by the National Academies of Sciences, Engineering, and Medicine (2018) typifies the perspective found in federal science agency reports and much science policy literature that postdoc training is too narrowly focused:

> [A] set of issues . . . concerns the nature of the training young scientists receive, and the mismatch between that training and their career prospects. 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.

[3]This "task approach" to labor markets has proved valuable in explaining a range of phenomena including wage

to associate workers with both their labor market outcomes and the actual tasks they perform on the job.[4] We use the NSF's Survey of Doctorate Recipients (SDR) to track both the salaries and *individual-level* job tasks of a nationally-representative and longitudinal sample of biomedical doctorates graduating in the US, where novel information on the evolution of each doctorate's job tasks enables a direct comparison of the skills acquired during postdoctoral training to the activities performed as part of future employment. We find that a positive postdoc salary premium emerges when the mismatch between current job tasks and those performed as part of postdoc training ("task mismatch") is low and a negative postdoc premium when task mismatch is high.[5] Controlling for individual-level measures of accumulated task-specific human capital reduces the estimated industry postdoc salary penalty by 66%, eliminating its statistical significance. In contrast, we find no evidence that general ability bias, compensating differentials for tasks performed as part of current employment, seniority, or employer size explains the postdoc salary penalty in industry. Altogether, our results indicate that differences in accrued task-specific human capital are an important source of wage variation among highly-skilled workers, so much so that the positive salary returns associated with the greater ability of postdoc-trained biomedical doctorates at graduation are greatly eclipsed by the negative effects of the mismatch between the tasks performed as part of postdoc training and the skills required on-the-job in industry.[6]

Beyond Stinebrickner, Stinebrickner, and Sullivan (2019) who track the tasks and salary of two cohorts of Berea College students over time, ours is the only other paper to our knowledge to track

variation among workers of the same education and occupation (Autor and Handel, 2013; Deming and Kahn, 2018; Stinebrickner, Stinebrickner, and Sullivan, 2019), the comparatively flat age-earnings profile of college graduates majoring in fast-changing technology-intensive subjects (Deming and Noray, 2020), life-cycle earnings and the impact of job mobility (Lazear, 2009; Gathmann and Schönberg, 2010; Sanders, 2016; Lise and Postel-Vinay, 2020; Guvenen et al., 2020), patterns in within-firm job promotions (Gibbons and Waldman, 2004), taste-based discrimination and changes in the Black-White wage gap (Hurst, Rubinstein, and Shimizu, 2021), employment and earnings polarization due to trade and technological change (Autor, Levy, and Murnane, 2003; Acemoglu and Autor, 2011; Autor and Dorn, 2013; Autor, Dorn, and Hanson, 2013; Acemoglu and Restrepo, 2021), jobless recoveries and employer "upskilling" following recent recessions (Hershbein and Kahn, 2018; Jaimovich and Siu, 2020), and the remote work capability of workers and COVID-19 job losses (Montenovo et al., 2020; Davis et al., 2021*b*). 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. See Acemoglu and Autor (2011) for an overview of the related literature on the relationship between technological change, job tasks, and US labor market trends.

[4]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. 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 the wages of two cohorts of Berea College students, finding strong evidence for learning-by-doing for "high-skilled" (but not low-skilled) tasks.

[5]In a Mincerian framework where we treat postdoc training as a general form of labor market experience, we find that the returns to postdoc training vary from a positive premium of 15.9% in academic non-tenure-track (non-TT) research jobs to a negative premium (or penalty) of 15.8% in industry jobs. These premia are *within-sector* premia, as it is the case that the pecuniary returns associated with industry employment typically exceed those in academia by a sizable margin. Task mismatch explains the variation in the within-sector returns to postdoc training across sectors (i.e., why postdoc training has a positive premium in academic non-TT research jobs but a negative premium in industry jobs).

[6]Bias-adjusted treatment effect estimates (using the Oster (2019) estimator) of the returns to postdoc training in industry suggest a greater ability of postdocs at time of PhD compared to their nonpostdoc-trained counterparts.

both the outcomes and tasks performed by the same workers longitudinally, rather than relying on external occupation- or job-level survey data to infer the history of tasks performed by each worker. Job tasks vary substantially within occupations (Autor and Handel, 2013; Deming and Kahn, 2018), with workers tending to match to jobs within a given occupation that minimizes the distance between the tasks of the job and the skill of the worker. Thus, assigning tasks to a worker based on occupation or job title will tend to overstate the distance between the worker's skill set and the tasks actually performed. Workers within a given occupation may also perform different tasks over their career, such as taking on more managerial tasks while retaining the same occupational title, and so longitudinal measures of worker-level tasks carry additional appeal. Other task-based studies analyze workers across a broad spectrum of occupations and categorize tasks into coarse categories such as abstract, routine, and manual. We show that skill-job mismatch is important even within a narrow education category (doctoral degree holders in the biomedical sciences) and within jobs that make nearly exclusive use of abstract/analytical ability.[7] Our findings suggest the importance of distinguishing between different types of analytical tasks when considering task-specific human capital models of wage determination, especially among highly-educated workers.

The structure of biomedical science gives a natural setting for exploring the pay-impacts of analytical task mismatch: the subsidization of academic postdoc positions focused on basic research paired with the limited number of permanent basic research positions in academia thereafter (such as tenure-track research positions) leads to a significant share of this labor force moving into nonacademic jobs that emphasize a different set of abstract tasks beyond basic research.[8] 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), but that post-postdoc employment shows considerable heterogeneity in tasks, with basic research being the most important task only in academic jobs. In industry jobs, managing people or projects, applied research, development, and professional services are all reported as more important activities, with only 10% of postdoc-trained industry workers primarily engaged in basic research. Postdoc-trained biomedical doctorates face the highest degree of task mismatch when transitioning to industry compared to other sectors, with the sizable postdoc salary penalty in industry highlighting an important trade-off between postdoctoral training and on-the-job training in industry for early-career

[7] While studies of education-job match quality have typically focused on the effects of overeducation and undereducation—where education is measured as whether the worker has a college degree and the education-job match is determined by whether the worker's job is typically held by workers of the same educational attainment—recent studies have examined mismatches among workers of the same level of educational attainment: Nordin, Persson, and Roof (2010) examine the consequence of mismatches among the college-educated, measuring the quality of the match by whether the worker's job is typical of persons who share the worker's major, and other works (e.g., Robst, 2007) use the worker's self-reported subjective measure of job match. To our knowledge, ours is the first work to measure education-job mismatch by relating the skills workers acquire during academic training—as measured by the performance of the tasks that comprise that training—to activities performed in later employment. This measure allows for differences in mismatch among workers within the same field of study and same level of educational attainment without relying on subjective measures of mismatch.

[8] In fact, we find that the share of postdoc-trained biomedical doctorates working in industry at ten years post-PhD (28%) exceeds the share working as tenure-track researchers (23%).

doctorates in biomedical science.[9]

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; Cheng, 2021). 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 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 following the postdoc. Meanwhile, among biomedical doctorates working in industry, we find that those with postdoc training are 12.3 percentage points more likely to obtain a research position within industry. However, 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 that persists for up to 15 years post-PhD. In contrast, we find no general postdoc salary penalty in academia, and instead find that postdoc training leads to a substantial salary premium (15.9%) for those who go on to work as non-tenure-track researchers.[10] 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. Our findings resolve an empirical puzzle in the literature: despite evidence that biomedical doctorates who pursue postdoctoral ("postdoc") training are of higher ability at graduation (Sauermann and Roach, 2016), they typically earn *less* than their nonpostdoc-trained counterparts, even within the same sector of employment (Kahn and Ginther, 2017). The negative pecuniary return to postdoctoral training has brought into question whether such training is consistent with a model of human capital investment; our study provides affirmative evidence, showing that a *task-specific* human capital framework explains both the between-sector heterogeneity in the returns to postdoctoral training and the sizable negative returns to postdoctoral training in industry.

The remainder of the paper is structured as follows: Section 2 gives a brief description of

[9] See Hayter and Parker (2019) for a survey-based qualitative study of the difficulties faced by postdocs transitioning to nonacademic positions. From section 5.1.3 therein: "Employers report that postdocs are adept at scientific concepts and research methods..." but that "... it is difficult for postdocs to learn how to apply their research skills in support of product development (in industry) or address a specific applied problem (in government labs). Postdocs do not possess leadership and teamwork experience required for industry or startup teams that integrate multiple functions, such as research, management, manufacturing, and sales. Associated skills include the capability to work under strict deadlines and budgets, cancel projects that do not yield results within a specific period, make brief pitches, and communicate complex concepts to non-scientific audiences.... [M]ulti-dimensional skills and swift transitions are particularly important within entrepreneurial ventures, given the rapid pace of change and need to quickly demonstrate results to investors."

[10] We find a salary penalty as in Kahn and Ginther (2017) when the employment sector is defined as that held by a PhD at ten years post-PhD, but find a salary premium in our preferred specification that defines the employment sector as that actually held by the PhD in each year. Only 58% of PhDs in our sample who were ever observed in academic non-TT research jobs were employed in such jobs at ten years post-PhD, implying significant mobility into and out of this subsector.

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, compares the tasks performed as part of postdoc training with those performed on-the-job by nonpostdoc-trained biomedical doctorates early in their career, and lays out our baseline empirical approach to estimating postdoc salary premia. Section 5 reports our baseline estimates of sector-specific postdoc salary premia that exclude task-based variables from the specification, and Section 6 gives our results when including task-based variables as part of the regression specification, either in the form of separate measures of the history of each task performed by workers as part of previous employment or as a single measure 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). Section 7 summarizes our main results and Section 8 concludes.

2 Postdoc Training: Apprenticeship or Lottery Ticket?

Biomedical research is a significant source of knowledge creation in the United States, representing a large portion of academic research activities and innovation.[11] Every year, a new crop of talented young biomedical PhDs graduate in the US and enter the job market in search of academic careers: 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).[12] Graduate students and postdocs are key labor inputs for the labs of research faculty and are responsible for conducting the "great majority of biomedical research" (Alberts et al., 2014). 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-

[11]Biomedical research expenditures represented 18% of all academic R&D expenditures in 2016 at just over 13 billion dollars. Life scientists produced almost half of all US university-based patents in 2016, with Pharmaceuticals, Biotechnology, and Medical Technology representing the top three technology areas covered by US university-based patents in 2016 (National Science Board, 2018). The COVID-19 pandemic and associated deep recession have exemplified the importance of biomedical innovation— and thus the biomedical PhD workforce—to economic performance and growth, with the rapid development of novel mRNA vaccines playing a fundamental role in the economic recovery.

[12]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.

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).

Nevertheless, while biomedical PhDs say they are in postdocs to obtain tenure track research job (Sauermann and Roach, 2016), most biomedical postdocs are unlikely to obtain one, with less than 20% of biomedical PhDs who graduated in 2005 working as a tenure-track researcher by 2015 (Figure A.5). This growth in the number of biomedical postdocs, paired with declining rates in the share eventually obtaining tenure-track positions, has attracted much concern from economists and biomedical researchers alike.[13] While postdoc training is much like an apprenticeship 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.6), and 40% of those employed in academia find themselves in jobs where research is not the primary focus (Figure A.7). 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.

Figure 1 plots the median salary of biomedical doctorates in academia, industry, and government/nonprofits by postdoc-trained status and years since PhD graduation.[14] As expected, postdoc-trained biomedical doctorates in industry, academia, and government/nonprofits 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. The median salary of ex-postdocs in academia and government/nonprofits appear similar to the median salary of nonpostdocs in these sectors, while in industry the gap between the median salary of postdoc-trained and nonpostdoc-trained biomedical doctorates is large and persistent, with ex-postdocs earning less than nonpostdocs. This pattern is consistent with industry-bound postdocs not only forgoing higher salary in industry during their years working as a postdoc, but also deferring

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

[14] For this figure, biomedical doctorates are associated with the employment sector (academia, industry, or government/nonprofits) 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.

task-specific human capital accumulation in tasks that are valued in industry but not emphasized as part of postdoctoral training, leading to lower (after-postdoc) salary in industry compared to nonpostdoc-trained biomedical doctorates. To formalize this intuition, in Section 3 we offer a simple task-specific human capital model of wage determination and apply this framework to explain salary differences between postdoc-trained and nonpostdoc-trained biomedical doctorates working in industry.

3 A Task-Based Framework of Wage Determination

Our conceptual framework represents a dynamic extension of the model in Autor and Handel (2013) where workers augment their skills over time through the performance of tasks. We write worker i's stock of skills at time t as $\Phi_{it} = \{\phi_{it}^1 \dots \phi_{it}^J\}$ 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 $k \in \{1, \dots, K\}$ by utilizing task-specific skills ϕ_{it}^j for $j \in \{1, \dots, J\}$ 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 and where all tasks are performed simultaneously as part of production in each unit of time. 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):

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

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 between workers in sector k are the result of differing levels of endowed and/or accrued task-specific human capital.[15]

[15] We note that it is possible that differences in task-specific human capital do not lead to differences in wages,

We assume that task j specific human capital accrual is the result of learning in previous employment (including postdoctoral training) such that:

$$H_{it}^{j} = \theta_{it}^{j} \tau_t, \tag{5}$$

where τ_t gives the number of years spent in previous employment as of year t and θ_{it}^{j} denotes the amount of task j specific human capital accrued per each unit of time performing task j multiplied by the share of years of previous employment spent performing task j.[16] Substituting (5) into (4), we get:

$$w_{ikt} = \alpha_k + \sum_j \lambda_k^j \theta_{it}^j \tau_t + m_{ik}, \tag{6}$$

where $m_{ik} = \sum_j \lambda_k^j H_i^j$ represents worker-sector match quality which is a function of worker skill endowments and sector-specific returns to skills. 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.

Suppose now that there are two tasks: research (R) and nonresearch (N). Also suppose there are two sectors—academia (A) and industry (I)— and for simplicity assume that all workers in the same sector k accrue task j specific human capital at the same rate so that $\theta_{it}^j \equiv \theta_k^j$. We index sectors of *previous* employment by k' and index the current sector of employment by k as before. Letting $\tau_{ik't}$ give the number of years worker i spent in sector k' as part of previous employment as of year t, equation (6) can be written as:

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

Also suppose that there are two types of workers p and n of the same level of overall experience (i.e., $\sum_{k'} \tau_{pk't} \equiv \tau_{pt} = \tau_{nt} \equiv \tau_t$) and who both work in industry. Suppose worker p spent all previous years in the academic sector as a postdoc while worker n has worked in industry ever since PhD graduation. Then we have the following:

$$\begin{aligned} w_{pIt} &= \alpha_I + \lambda_I^R \theta_{A'}^R \tau_t + \lambda_I^N \theta_{A'}^N \tau_t + m_{pI}, \\ w_{nIt} &= \alpha_I + \lambda_I^R \theta_{I'}^R \tau_t + \lambda_I^N \theta_{I'}^N \tau_t + m_{nI}, \end{aligned}$$

where $m_{ik} = \lambda_k^R H_i^R + \lambda_k^N H_i^N$. Then wage differences between workers are due to differences in endowed task-specific human capital and differences in accrued task-specific human capital caused by $\theta_{A'}^R \neq \theta_{I'}^R$ or $\theta_{A'}^N \neq \theta_{I'}^N$.[17]

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

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.

[16] A simple proxy for θ_{it}^j is the share of years of previous employment spent performing task j.

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

as the following:

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

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. 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.[18]

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 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.[19] A unique aspect of SDR data is that it also includes, for each doctorate, the primary and secondary tasks associated with current employment and with postdoc spells, 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.[20] For doctorates in the constructed longitudinal SDR 1993-2017 dataset, we pull any

[18] 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 two 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.

[19] 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`.

[20] Primary and secondary tasks reflect the two tasks that each doctorate reports as occupying the most and second-most time during the typical work week. 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

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 that contains, among other information, each PhD recipient's field of study and whether he/she intended to take a postdoc position after graduation.[21] 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.[22] 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.[23] 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 the first six years post-PhD as well as any years when a doctorate is employed as a postdoc. 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.[24] Table 1 breaks down the analytical sample by sector and subsector of employment and whether biomedical doctorates within each sector are postdoc-trained. The first three columns assign each doctorate to the employment sector they occupy at ten years post-PhD while the last three columns assign each person-year observation to the actual sector of employment in each given year, thus allowing each doctorate to occupy different sectors of employ-

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.

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

[22] See Appendix B for details.

[23] 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. The SDR 2010 wave also 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.

[24] "Research job" includes jobs where the primary activity is reported as either basic research, applied research, development, or design, following the NSF's categorization of "research and development" activities. Tenure-track workers include those on the tenure-track and those who have received tenure.

ment in different years.[25] Panel A gives the number of person-year observations and unique persons in each sector by postdoc-trained status, and Panel B gives the row, column, and total share of unique persons in each cell as calculated from Panel A.[26] 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. Academia employs the highest share of biomedical doctorates by ten years post-PhD (53%), followed by industry (31%) and government/nonprofits (16%). Within academia and industry, jobs that require research as the primary work activity have greater shares of postdoc-trained workers. Interestingly, the share of postdoc-trained biomedical doctorates employed in industry at ten years post-PhD (28%) exceeds the share employed in tenure-track research positions (23%). Differences in the person counts between the third and last columns 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.[27]

Table 2 reports summary statistics for the analytical sample broken down by postdoc-trained status and current employment sector.[28] 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.

4.2 Task Differences Between Postdoc Training and Other Employment

Table A.2 shows substantial differences between postdocs and nonpostdocs in the tasks reported as primary work activities at least once in the first six years post-PhD.[29] Approximately three-

[25]The observation counts in the last three columns of Table 1 exclude observations corresponding to years when a biomedical doctorate is employed as a postdoc and any years within the first six years post-PhD.

[26]For clarity, the first column of the "Industry" row in Panel B shows that 65% of biomedical doctorates working in industry at ten years post-PhD are postdoc-trained, representing 28% of total biomedical postdoc-trained employment and 20% of total biomedical doctoral employment, respectively.

[27]See Panel C for these calculations for each employment sector by postdoc-trained status.

[28]Doctorates who switch employment sectors during their careers will appear in multiple employment sector samples.

[29]For the comparisons in Table A.2 and Figure 2, we restrict the sample to biomedical doctorates who are employed in the given sector of employment at 10 years post-PhD and whose tasks we observe at least two times during the first six years of post-PhD employment (including postdoc training); 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. 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

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 depending on employment sector. 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. For both postdoc-trained and nonpostdoc-trained biomedical doctorates that work in industry at 10 years post-PhD, the first panel of Figure 2 shows the percentage of each that reports working in a job where at least 10% of work time is spent engaged in each given task in any of the first six years post-PhD.[30] 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 development, design, management, and professional services (among other tasks) during their postdoc training, giving nonpostdocs working in industry during their first six years post-PhD a better opportunity to develop skills in these tasks early in their career. The stark differences in the job tasks performed by biomedical postdocs and nonpostdoc-trained biomedical doctorates working in industry early in their career are consistent with postdoc training and on-the-job learning in industry acting as distinct training regimens that 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 be paid less than a worker whose previous job had more similar task requirements (Gathmann and Schönberg, 2010). Thus, in Figure 2 we also show 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 take the difference between the share performing each task during and after the first six years post-PhD and report this percentage-point difference as the "Task Change." Figure 2 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. 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) likely explains some part of the postdoc salary penalty in industry that we observe in Figure 1. Figure A.8 shows task changes by employment sector for postdoc- and nonpostdoc-trained workers. Comparing the magnitudes in the left and right

to years where the person is employed in the given employment sector.

[30]See Table A.3 for the underlying data plotted in Figure 2 and see Table A.4 for comparable data on biomedical doctorates working in the academic and government/nonprofit sectors at ten years post-PhD.

panels, we see that postdoc-trained workers tend to experience greater task changes compared to nonpostdoc-trained workers regardless of employment sector. Task changes facing postdocs are larger in industry than in the other sectors for 10 of 14 tasks, while task changes for nonpostdoc-trained workers in industry are only the largest for 2 of 14 tasks, underscoring the greater degree of mismatch faced by postdocs transitioning to industry—both in comparison to other sectors and to nonpostdoc-trained doctorates working in industry.

4.3 Empirical Specification

Before exploring the degree to which task mismatch explains postdoc salary premia, we must first estimate postdoc salary premia in the absence of controls for the tasks performed as part of previous employment.[31] Our preferred specification for estimating the postdoc salary premium in each sector is given by the following person-year level Mincer equation:

$$\log(earn_{ifsct}) = \boldsymbol{X_i}\boldsymbol{\beta} + \theta Postdoc_i + \boldsymbol{Exp_{it}}\boldsymbol{\lambda} + \boldsymbol{\gamma_{fc}} + \boldsymbol{\gamma_s} + \boldsymbol{\gamma_t} + \varepsilon_{ifsct}, \tag{9}$$

where $earn_{ifsct}$ is the year t inflation-adjusted annualized salary of doctorate i who graduated with a PhD in field f from university s in year c, $\boldsymbol{X_i}$ is a vector of pre-determined individual-level controls, $Postdoc_i$ is an indicator variable for if doctorate i is postdoc-trained, $\boldsymbol{Exp_{it}}$ is a vector containing a quartic polynomial in experience, $\boldsymbol{\gamma_{fc}}$ are field-by-cohort fixed effects, $\boldsymbol{\gamma_s}$ are PhD institution (i.e., *alma mater*) fixed effects, $\boldsymbol{\gamma_t}$ are normalized year fixed effects, and ε_{isfct} is an idiosyncratic error term.[32] 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 controls for 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.[33] Field-by-cohort fixed effects ($\boldsymbol{\gamma_{fc}}$) control for field-cohort specific shocks that could influence both a doctorate's decision to pursue a postdoc and future career outcomes.[34]

[31] We discuss the construction of individual-level longitudinal measures of each doctorate's stock of accrued task-specific human capital, as well as a measure of the distance/mismatch between tasks performed as part of current and past employment, in Section 6.

[32] Salary is adjusted using the CPI-U. 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.

[33] See Table A.5 for the list of controls. See Table A.6 for results from a person-level regression of the postdoc indicator on the time-invariant controls.

[34] 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

PhD institution (i.e., *alma mater*) fixed effects ($\boldsymbol{\gamma_s}$) 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 postdoc salary premia 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.[35] As it is well-known that postdocs get paid less than nonpostdocs throughout the duration of their postdoc employment, we consider a subsequent analysis where, for postdoc-trained doctorates, we include only observations for years after their postdoc training has ended.[36] 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 enables grouping of 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 prone to 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. This allows the shape of the predicted salary profiles to vary based on one's postdoc-trained status.

We then consider an alternative specification where experience is 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 graduation (as before).[37] This specification is useful for measuring disparities in entry-level salaries of postdoc-trained and nonpostdoc-trained biomedical doctorates

learning methods in biomedical research) that open up both new avenues for research and new economic opportunities. For example, see the large increase in the number of NIH-supported PhD recipients in neuroscience and neurobiology since the 1990s: `https://report.nih.gov/nihdatabook/report/267`.

[35] 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.

[36] 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. There are very few after-postdoc observations for postdoc-trained biomedical doctorates at the lowest levels of experience, and so failing to drop the first six years post-PhD for all doctorates would lead to salary-experience profiles at the lowest levels of experience being driven by nonpostdoc observations almost exclusively.

[37] 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.

and is akin to treating postdoctoral training as a form of education (or "schooling").[38] 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.

We also analyze the relationship between postdoc training and the likelihood that biomedical doctorates obtain research jobs in academia and industry. Our empirical model is given by the following person-level linear probability model (LPM) specification:

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

where job_{ifsc} is an indicator variable for if doctorate i who graduated with a PhD in field f from university s in year c ever obtains a given research job and all other variables are defined as before. We consider five different indicator variables: The first is for whether a doctorate ever finds any type of nonpostdoc research position ("any"), the second is for whether a doctorate ever finds a nonpostdoc research position in academia ("academic"), the third is for whether a doctorate ever lands a tenure-track research job in academia ("tenure-track"), the fourth is for whether an individual obtains tenure in an academic research position ("tenured") conditional on having obtained a tenure-track research position, and the fifth is an indicator variable for if a doctorate ever obtains a research position in industry conditional on ever working in industry ("industry"). 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 may not 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 C.1 for a discussion of this method, followed by the estimation of bias-adjusted versions of the results that follow.

[38] In a Mincerian framework, (potential) experience is typically defined so as not to include years of schooling. Like doctoral training, postdoctoral training typically takes place at a US university, is tuition-free (from the perspective of the trainee), 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. One might argue that postdoctoral training should be treated as a form of schooling given that the decision whether to pursue postdoc training is similar to the decision faced by Bachelor's degree holders deciding between industry employment or investing in doctoral education. A task-based approach is useful in resolving the debate between "postdoc as labor market experience" versus "postdoc as schooling" (or, equivalently in our context, as its own form of experience) by positing that the performance of tasks, whether on-the-job or through formal education training, leads to the accumulation of human capital specific to the skills utilized in the tasks performed, and so it is the tasks performed as part of schooling and employment, rather than whether a thing is classified by the researcher as "schooling" or "employment," that matters.

5 Baseline Results

5.1 Postdoc Salary Premium by Employment Sector

Table 3 reports salary regression results where an indicator variable for if a biomedical doctorate ever received postdoc training serves as the main variable of interest. We primarily focus attention to results in columns (2), (4), and (6), with columns (1), (3), and (5) allowing the reader to gauge the sensitivity of results to inclusion of field-by-cohort and PhD university fixed effects. Columns (1) and (2) report results from regressions that include all person-year analytical sample observations, including observations corresponding to years when a biomedical doctorate is employed as a postdoc, and where we follow Kahn and Ginther (2017) in defining the employment sector as that observed at 10 years post-PhD. 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 vary widely across sectors of employment: postdoc-trained biomedical doctorates in academia earn about 6.0% less than their nonpostdoc-trained counterparts (Panel B), while a postdoc-trained biomedical doctorate who works in industry faces a larger 21.3% postdoc salary penalty (Panel C). Since the sample underlying column (2) results includes salary observations in years when a biomedical doctorate is employed as a postdoc, some of the difference in the magnitude of the estimates between the industry and academic employment sectors is likely driven by the higher starting salaries in industry as shown in Figure 1.

To explicitly test whether postdoc training impacts *after-postdoc* salary, columns (3) and (4) report results from regressions where 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 any and all postdoc positions. We also drop observations corresponding to a person's first six years post-PhD to make the set of postdoc and nonpostdoc observations comparable (see Footnote 36 for more detail). We then associate each person-year observation with the employment sector held by each doctorate in the given year (i.e., the "current" employment sector), rather than defining the employment sector for each doctorate at a single point in time. 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. We find that if a postdoc lands a position in academia, then he or she does not face a postdoc penalty on future salary; in contrast, postdocs going on to careers in industry or government/nonprofits face a 15.8% and 10.6% penalty on after-postdoc salary, respectively.

The estimates reported in columns (1) through (4) of Table 3 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 emphasize different sets of skills, we would expect within-cohort differences in accrued task-specific human capital between ex-postdocs and nonpostdocs working in industry, resulting in salary differences. If postdoc training is instead treated as a type of schooling such that experience is defined as the number of years in post-PhD nonpostdoc employment, we would not expect such differences—continuing our example, rather than comparing the entry-level salary of a postdoc-trained biomedical doctorate with the salary of a nonpostdoc-trained doctorate with six years of industry experience, defining experience in this way compares the entry-level salary (and salary since year of entry) of both types of biomedical doctorate in industry. Therefore, we estimate specifications (5) and (6) which are identical to specifications (3) and (4), respectively, except that experience is defined as the number of years in post-PhD nonpostdoc employment.[39] We find that the postdoc penalty on salary in industry is no longer statistically significant when experience is defined in this way, and also find that postdoc training is associated with a statistically significant 9.8% *increase* in salary in academia. This suggests that entry-level salaries in industry are not much different for postdoc-trained and nonpostdoc-trained biomedical doctorates, and that the industry postdoc salary gap in column (4) might be explained by postdocs delaying their entry into industry and thus deferring the accumulation of task-specific human capital in those tasks important for industry employment.

5.2 Allowing for Dynamics in Postdoc Salary Premium

Since the impact of postdoc training on salary might vary over a person's career, we consider augmented versions of the specifications underlying columns (2), (4), and (6) that allow for interactions between the indicator variable for postdoc training and the quartic polynomial in years of experience. We use the results from such regressions to generate predicted salary profiles for postdoc-trained and nonpostdoc-trained biomedical doctorates.[40] Figure 3 plots the predicted salary profiles generated from the augmented version of specification (4) which only includes after-postdoc salary observations and where each observation is associated with the current employment sector.[41] Figure 3 shows that postdoc training is associated with a persistent after-postdoc salary penalty in industry. In academia, postdoc training appears to have a slight negative impact on future salary early in a doctorate's career but enhances salary growth so that the salary of postdoc-trained biomedical doctorates catches up and then exceeds that of their nonpostdoc-trained counterparts

[39] One other difference is that in columns (5) and (6) regressions we do not remove observations corresponding to the first six years post-PhD for nonpostdoc-trained biomedical doctorates.

[40] 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 with 95% confidence intervals.

[41] See Figure A.9 for predicted salary profiles generated from the augmented version of specification (2) which includes salary observations in postdoc years and defines employment sector subsamples based on the sector of employment held by each doctorate at 10 years post-PhD.

after about 15 years post-PhD.[42] Figure A.10 plots the predicted salary profiles generated from the augmented version of specification (6) which measures experience as years of nonpostdoc employment rather than years since PhD (and thus treats postdoc training as schooling). Figure A.10 shows that when experience is defined in this way, postdoc training is associated with a persistent increase in salary for academic jobs, but does not significantly impact salary in industry or government/nonprofits.

Altogether, our 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 (4) of Table 3 is driven by differences in the accumulation of industry-relevant human capital between postdoc-trained and nonpostdoc-trained biomedical doctorates early in their career. Results in column (6) indicate that postdoc-trained and nonpostdoc-trained biomedical doctorates earn similar entry-level salaries in industry and government/nonprofits and that their salary trajectories follow similar patterns after entry, but that postdoc training might improve one's chances of obtaining a higher-paying academic research-based job.

5.3 Postdoc Training and Obtaining a Future Job in Research

To examine 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 any nonpostdoc research job, 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. Table 4 reports the results using the LPM specification given by equation (10). We find that doing a postdoc increases the likelihood of working in any research job by 24.2 percentage points, an academic research position by 26.5 percentage points, and a tenure-track research position by 21.3 percentage points.[43] Among those that ever take a tenure-track job and whom we observe after they are up for their tenure decision, we find that postdoc training does not significantly impact the ability of tenure-track researchers to obtain tenure.[44] Lastly, among doctorates who ever work in industry, we find that postdoc training raises the probability of obtaining a research position in industry by 12.3 percentage points.

5.4 Postdoc Salary Premium 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

[42] 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.

[43] Table A.7 shows that, more generally, postdoc-trained biomedical doctorates are more likely to land academic jobs, including tenure-track jobs, but that the estimated effects of landing *research-focused* academic and tenure-track jobs (as shown in Table 4) are greater by comparison.

[44] 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.

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 5. Focusing on specification (4) which limits the sample to after-postdoc salary observations, we find 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 like schooling (i.e., when experience is defined as years of post-PhD nonpostdoc employment) in column (6).

As with industry, we partition academia into the same subsectors as in Kahn and Ginther (2017): "academic tenure-track (TT) research", "academic non-tenure-track (non-TT) research", and "academic nonresearch." Column (4) results suggest that postdoc-trained biomedical doctorates 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 treating postdoc training as 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 is likely due to similarities in the set of tasks emphasized in both types of jobs.[45]

Figure 4 plots predicted salary profiles generated from augmented versions of specification (4) that allow for interactions between the indicator variable for postdoc training and the quartic polynomial in years of experience.[46] The salary advantage of postdoc-trained biomedical doctorates in academic non-TT research appears relatively stable over time but is estimated with less precision at high levels of experience. The postdoc penalty in industry research lasts for over ten years post-PhD, but appears to dissipate over time; in contrast, the postdoc penalty in industry nonresearch jobs appears persistent.

5.5 Robustness Check: Selection on Unobservables

In Appendix C.1, we describe and 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 (4) and (6) of Table 3 and Table 5 and the research job results in Table 4. We find that both the

[45]See Section 5.5 for evidence against a selection on unobserved ability at time of PhD explanation. In column (2), 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 who run similar regressions, 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 subsector when comparing results in columns (2) and (4).

[46]See Figure A.11 and Figure A.12 for predicted salary profiles generated from augmented versions of specification (2) and (6), respectively.

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.[47] Altogether, these results suggest that ability bias is unlikely to explain the existence of a postdoc penalty in industry, and that the true salary penalty in industry caused by postdoc training is somewhere between 15.8% (i.e., the estimate in column (4) of Table 3) 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.

In Panel B column (4) of Table 5 we find that postdoc-trained biomedical doctorates working as non-TT academic researchers tend to earn more than their nonpostdoc-trained counterparts. While this may suggest that postdoc training increases the productivity of non-TT researchers, one might wonder whether it is explained by ability bias—that is, if biomedical doctorates who pursue postdoc training tend to be of greater ability at graduation, then it could be the case that postdoc-trained biomedical doctorates earn more than nonpostdoc-trained PhDs in non-TT research jobs even if postdoc training imparts no skills (human capital) beyond PhD training. However, in Table C.2 we find that the bias-adjusted estimate of the effect of postdoc training on salary in non-TT research jobs exceeds the non-bias-adjusted estimate, meaning that selection bias pushes the estimate in a *negative* direction. This suggests that postdoc-trained biomedical doctorates who land a job in academic non-TT research are of lower average ability at time of PhD graduation compared to biomedical doctorates who forgo postdoc training and choose a job in non-tenure-track research directly after graduation.[48] This result is consistent with postdoc training being an effective way to augment skills relevant to academic research, rather than only serving as a holding tank.

6 Evidence for a Task-Specific Human Capital Explanation

A novel feature of the SDR is that it provides individual-level, longitudinal measures of tasks that are directly linked to the salary of the job for which these tasks are performed.[49] 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

[47]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).

[48]That is, while the average postdoc-trained biomedical doctorate is of higher ability than the average nonpostdoc-trained biomedical doctorate (including those who land in industry), the average postdoc who lands a non-TT research position is of *lower* ability at the time of PhD graduation compared to biomedical doctorates who forgo postdoc training to work as non-TT researchers directly after graduation.

[49]See Footnote 20 for the list of 14 work activities/tasks included in the SDR.

postdoc salary penalty.[50] We then construct a measure of distance 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. 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).[51]

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

Given the differences in tasks performed by postdocs and nonpostdoc-trained biomedical doctorates working in industry early in their career (see Section 4.2), we would expect those with the longest postdoc spells to experience the largest after-postdoc salary penalties in industry. This is what we find in column (4) of Table D.1 where biomedical doctorates with postdoc lengths exceeding six years experienced the largest industry postdoc penalties.[52] We would also expect the magnitude of the estimated postdoc penalty in industry to decrease when defining experience as years of post-PhD employment in nonpostdoc positions rather than as years since PhD graduation as 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. Indeed, column (6) of both Table 3 and Table D.1 shows that 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 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

[50] This estimate can be found in column (4) of Panel C in Table 3 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.

[51] 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. See Table A.8 for observation and person counts of biomedical doctorates in each employment sector for this sample which we use in our task regressions.

[52] See Appendix D for an analysis where we replace the single indicator variable for if a biomedical doctorate is postdoc-trained with three indicator variables based on whether a doctorate participated in postdoc training for 1) no longer than three years, 2) greater than three years but less than six years, and 3) exceeding six years. Table D.1 reports results when estimating postdoc salary premia and Table D.2 reports results on the relationship between postdoc length and the likelihood of obtaining a future research job.

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.[53] We estimate specifications using different combinations of these three sets of task history variables as a robustness check. While SDR data do not include the exact proportion of time spent on each task, they do indicate which tasks occupy the most and second-most time during the typical work week; thus, including primary or secondary task histories alongside the history of tasks performed for at least 10% of work time allows us to account in some way for differences in the time allocated to different tasks.

Table 6 Panel A shows that the estimated industry postdoc salary penalty is substantially reduced when including measures of the history of tasks performed by biomedical doctorates in previous jobs (including postdocs) 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).[54] Results are consistent across specifications, with point estimates declining by between 43% and 66% across all specifications. Table 6 Panel B shows that adding controls for current job tasks—rather than the history of job tasks—does little to change the estimated industry postdoc salary penalty; in fact, including controls for current job tasks increases (albeit slightly) the estimated postdoc salary penalty across all specifications. Together, these results support 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, rather than by compensating differentials for current job tasks.[55]

For insight into the importance of different types of accumulated task-specific human capital to industry salary determination, Table A.11 reports coefficient estimates for the primary task history controls included in specification/column (2) of Table 6, where each estimate measures 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 an approximate 4% decline in salary. Assuming constant returns to task tenure, this implies that a biomedical doctorate primarily engaged in basic research for five years (e.g.,

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

[54]Specification (1) in Table 6 is identical to specification (4) in Table 3, but is estimated on the set of doctorates in our analytical sample for whom we observe job tasks at least two times in the first six years post-PhD.

[55]See Table A.9 for regressions on the full sample and academic and government/nonprofit sectors where task variables are included. Addition of task history variables reduces the estimated postdoc salary penalty in the full sample by 41% in column (6) whereas addition of current job task controls has a minimal impact. The postdoc salary premia in academia and government/nonprofits estimated in regressions without the inclusion of task variables are statistically insignificant in our task regression sample.

as a postdoc) stands to lose 20% of their industry earnings capacity compared to the case where they obtain an applied research-focused job in industry upon graduation. Substituting a year of primary focus in applied research for a focus on teaching, sales/marketing, or accounting are all associated with declines in salary, while instead substituting for a year focused on managing people or projects is associated with an increase in salary. Experience in development, design, production, and professional services all yield similar returns to a year spent in applied research.

6.2 Task Mismatch and Postdoc Salary Premia Across Sectors

Next, we construct a single 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 postdoc salary premia 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 percentage 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 during the first six years. 3) We calculate the proportion 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.[56] 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 in current employment.[57]

To test whether task mismatch explains the difference in postdoc salary premia across sectors, we estimate a regression for all sectors as in Panel A Column (4) of Table 3 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

[56] 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

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

[57] While this measure of task distance is a rough approximation, it has the benefit of being based on tasks actually performed by each respondent—occupation-based measures of task distance (e.g., see 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 for one's own time spent on a task.

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.[58]

Column (1) of the "All Sectors" results in Table 7 shows that postdoc-trained doctorates tend to earn 8.2% less than their nonpostdoc-trained counterparts after controlling for average differences in salary across sectors. Allowing for the impact of postdoc training to vary by task distance in column (2), 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 who perform a set of tasks identical to those performed during postdoc training are paid the same as their nonpostdoc-trained counterparts, with task mismatch pushing 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 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 on average.[59] We find that after controlling for task mismatch, there is no residual difference in salary between postdoc-trained and nonpostdoc-trained biomedical doctorates, regardless of employment sector.

[58] 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 jobs and would expect increases in task mismatch to push the returns to postdoctoral training in a negative direction to account for the null or negative premia estimated for other sectors.

[59] A similar result holds for academic jobs, while the salary penalties associated with task mismatch in industry and government/nonprofits are particularly concentrated among ex-postdocs, suggesting that postdoc training might reduce one's match for industry or government/nonprofit jobs in ways that are correlated but not completely captured by our measure of task mismatch. It might also reflect a higher-chance that nonpostdoc-trained biomedical doctorates in these sectors experience a "positive" form of task mismatch that accompanies promotions into higher-paying jobs that entail different tasks than those performed during the first six years post-PhD. For example, Table A.2 shows that the share of nonpostdoc-trained doctorates in industry and government/nonprofit jobs ever reporting management as their primary work activity doubles after six years post-PhD.

7 Discussion of Results

We find that postdoc-trained biomedical doctorates in industry earn 15.8% less than their nonpostdoc-trained counterparts annually, controlling 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 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, seniority, or compensating differentials for conducting research or other tasks as part of current employment.[60] 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 are the result of differences in the history of tasks performed as part of 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 (by 66%), rendering the estimate statistically insignificant. We find that those who participate in postdoc training the longest suffer the largest postdoc salary penalties 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. Evidence suggests that the estimated 15.8% postdoc salary penalty in industry is a lower-bound for the true impact of postdoc training on industry salary, which suggests that biomedical doctorates who first pursue postdoc training prior to employment in industry are of greater ability at time of PhD graduation compared to their nonpostdoc-trained counterparts.

More generally, 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. Evidence suggests that the positive postdoc premium for academic non-tenure-track research is not the result of selection on unobserved ability at time of PhD graduation; while biomedical doctorates who pursue postdoc training tend to be of greater ability than those that do not (including those that later sort into industry positions), this appears not to be the case for biomedical doctorates who sort into academic non-tenure-track research jobs. Bias-adjusted estimates of the postdoc salary premium exceed 15.9%, implying that selection bias attenuates rather than exaggerates the impact of postdoc training on salary in academic non-tenure-track research positions. This result is consistent with postdoc training being an effective way to augment skills relevant to academic research, rather than only serving as a holding tank or as a signal of pre-existing ability. Indeed, postdoc-trained biomedical doctorates are better able to secure research-focused positions, both in academia and industry, compared to their nonpostdoc-trained

[60] See Appendix E for results pertaining to compensating differentials, sorting into firms and occupations, and seniority.

counterparts, with estimates robust to selection on unobserved ability at time of PhD graduation.[61]

A task-specific human capital explanation is consistent with the views of those within the biomedical community who argue both that postdoc training is specialized academic training and that initiatives to broaden the types of training and career preparation available to postdocs may be desirable given the growing number of biomedical doctorates working outside academia.[62] 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 jobs in industry.[63] While our results suggest that increasing the exposure of biomedical postdocs to skills valued in industry would be effective at lessening the postdoc salary penalty in industry, it is unclear whether a more "industry-oriented" postdoc would be of net benefit to society without a rigorous welfare analysis that lies outside the scope of the present paper.[64]

Whether postdoctoral training is of net benefit to postdocs themselves will depend on many factors, but having the requisite information to make such a decision is important. The findings in this paper suggest that postdoc training increases one's chances of obtaining an academic tenure-track research position by about 20% and an industry research position by 12%. Back-of-the-envelope calculations suggest that, on average, those headed to a career in industry after their postdoc will be paid $478,000 (undiscounted 2018 USD)—or $366,000 discounted annually at 3%—less in their first 20 years post-PhD than their nonpostdoc-trained counterparts who entered industry after graduation.[65] However, a postdoc who lands a job in industry will still be paid $489,000 ($339,000 discounted) more than the average postdoc who subsequently works in academia.[66] Combining results, the average postdoc-trained biomedical doctorate who works in academia earns $967,000 (undiscounted) less than the average nonpostdoc-trained biomedical doctorate working in industry

[61] Our results do not discount the role played by postdoctoral training as a place for doctorates to "queue" or compete for tenure-track positions or as a way to signal ability or preferences for research-based jobs. Rather, our results imply that postdoc training augments the academic research skills of trainees—in addition to any other roles it might play—and thus can be regarded as a (task-specific) human capital investment. For work focused on the other possible roles of postdoc training, see queuing models in which the postdoc acts as a holding room for biomedical PhDs awaiting tenure-track offers (Hur, Ghaffarzadegan, and Hawley, 2015; Andalib, Ghaffarzadegan, and Larson, 2018) and tournament models in which young doctorates compete through research effort in the labs of established researchers to win tenure-track positions (Freeman et al., 2001*a*,*b*).

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

[63] 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.

[64] Such an analysis, among other things, would need to quantify the impact of postdocs on academic output compared to industry output, and quantify the benefit of each type of output to society, factoring in knowledge spillovers.

[65] Calculations are based on combining the predicted salary profiles for the first six years post-PhD in Figure A.9 with the predicted salary profiles for subsequent years given in Figure 3.

[66] Compared to a postdoc who lands a tenure-track research position, postdocs in industry are paid $213,000 ($152,000 discounted) more in their first 20 years post-PhD.

in their first 20 years post-PhD, for an average of $48,350 less per year.

8 Conclusion

This paper makes contributions to the growing empirical literature in labor economics that views tasks as fundamental to human capital acquisition and wage determination. First, we identify a natural environment where a sizable share of workers experience large, abrupt dislocations between job tasks and task-specific skills (i.e., biomedical postdocs who transition to industry employment). The population we analyze—biomedical PhDs in the US—though a small and non-representative subset of the US workforce, is highly selected, with less heterogeneity across workers taking different paths compared to other studies of the effects of task mismatch on earnings. This allows us to produce estimates of the effect of task mismatch on earnings that are arguably less susceptible to selectivity bias. These estimates show that task mismatch is important to explaining between-sector heterogeneity in the returns to education of a given type in a case where such returns range from significantly positive to significantly negative.

Second, we study a case where skill mismatch is not due to a trade or technology shock, but is a foreseeable outcome of a risky human capital investment strategy to land a particular career. With the additional, highly specialized training of a postdoc, PhDs "purchase" a "lottery ticket" which sometimes pays off with an academic research career and job tasks well-matched to the PhD's skills, but often does not leading to careers where job tasks are not aligned with the skills honed in the postdoc. Other researchers have shown that PhDs pay for the opportunity to conduct research with lower wages (Stern, 2004; Sauermann and Roach, 2014).[67] We show that *ex ante* skill mismatch is another compensating differential for the opportunity to participate in science, finding that postdocs who end up in industry earn on average (discounted) $366,000 less in the first 20 years after their PhD compared to if they had gone directly to industry after graduation.

Many careers with high on-the-job consumption, such as in the arts, entertainment and sports, share this quality of requiring significant pre-career investments in non-transferable human capital to gain a small chance of access. In such careers skill mismatch occurs when workers finally turn to their "plan B." Skill mismatch may also arise *ex post* when young workers must make their human capital investments while still uncertain of their abilities or preferences, which may be the case also for some doctorates in the life sciences who choose postdoctoral training. We believe investigations into the relative importance of both types of skill mismatch in specialized labor markets would be fruitful.

Third, we show that differences in task-specific human capital are important to explaining lifetime earnings disparities among highly-skilled workers within the same field of study and employment sector, with our results highlighting an important trade-off between postdoctoral training

[67] We find that PhDs who go the postdoc route and "win" (that is obtain an academic position) earn (an undiscounted) $967,000 less than the PhD who goes directly into industry in the twenty years following the PhD.

and on-the-job training in industry for early-career biomedical doctorates. Ours is the only paper to our knowledge that exploits data on the task content of academic training itself to explain the effects of such training on the future salary of workers within the same field. Fourth, we find that distinguishing between different types of analytical tasks is valuable to explaining wage determination among highly-educated workers, with our results speaking specifically to the wage effects of "analytical task mismatch." Analytical task mismatch may be important for explaining between-sector heterogeneity in the returns to other forms of higher education of a given type (such as college degrees in a particular field), and so data collection on the type and intensity of analytical tasks performed by students during their academic training and subsequent career could be fruitful in examining within-field wage dispersion.

Lastly, we demonstrate the value of longitudinal data with information on both individual-level tasks and labor market outcomes. Most studies in the task literature rely on external occupation-level data to infer tasks performed by individual workers. Previous research shows that workers sharing the same occupational code are likely to be paid differently when each performs a different set of tasks (Autor and Handel, 2013), with occupation-level measures of tasks unable to capture such heterogeneity. Among workers performing similar sets of tasks in their jobs, we find that the history of tasks performed as part of previous employment or training is an important factor in wage determination, showcasing the value of longitudinal measures of worker-level tasks. Previous work by Stinebrickner, Stinebrickner, and Sullivan (2019) utilizing person-level and longitudinal measures of tasks was restricted to the study of students entering Berea College over the course of two years; our study demonstrates the broader relevance of task tenure to wage determination by utilizing a nationally-representative sample of biomedical doctorates graduating over the course of two decades.

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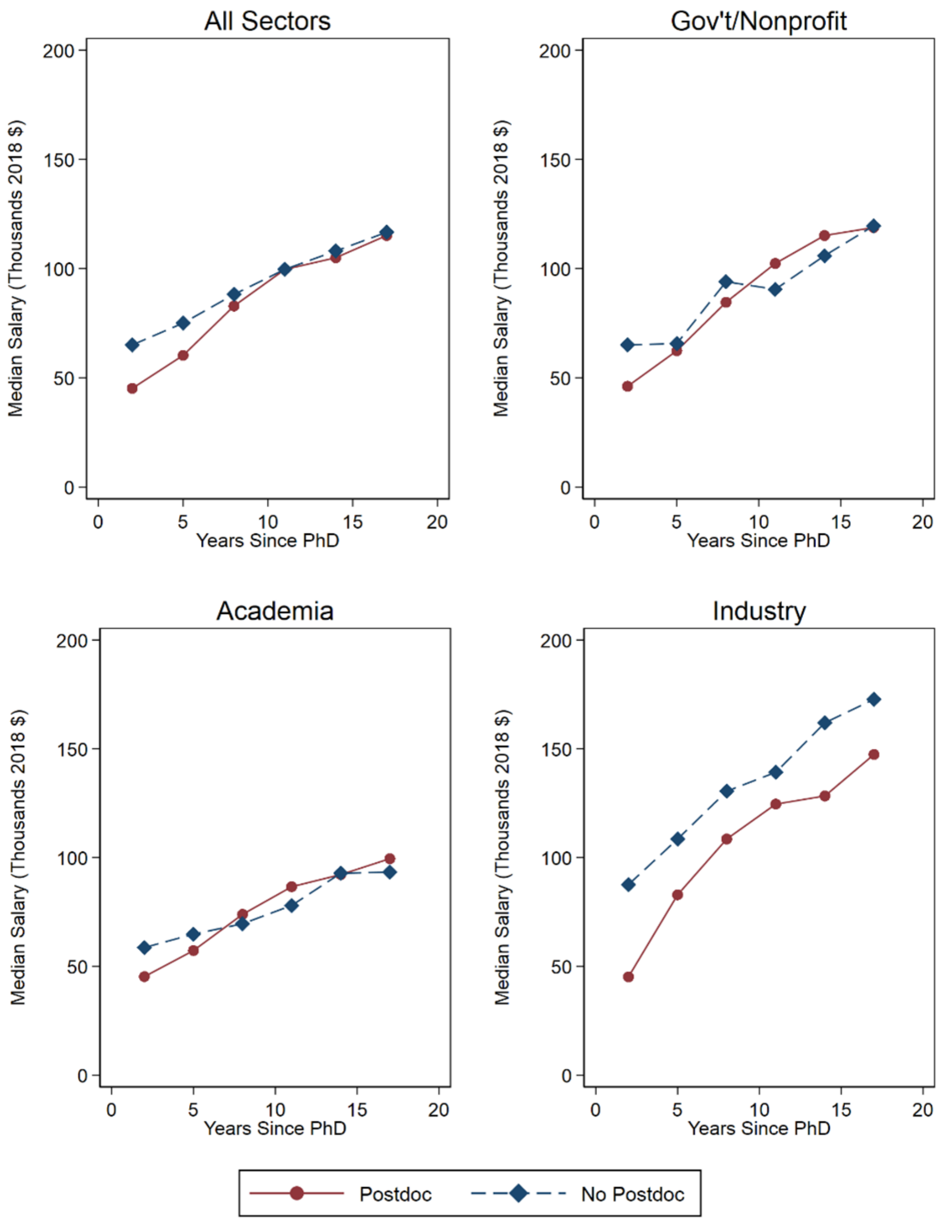
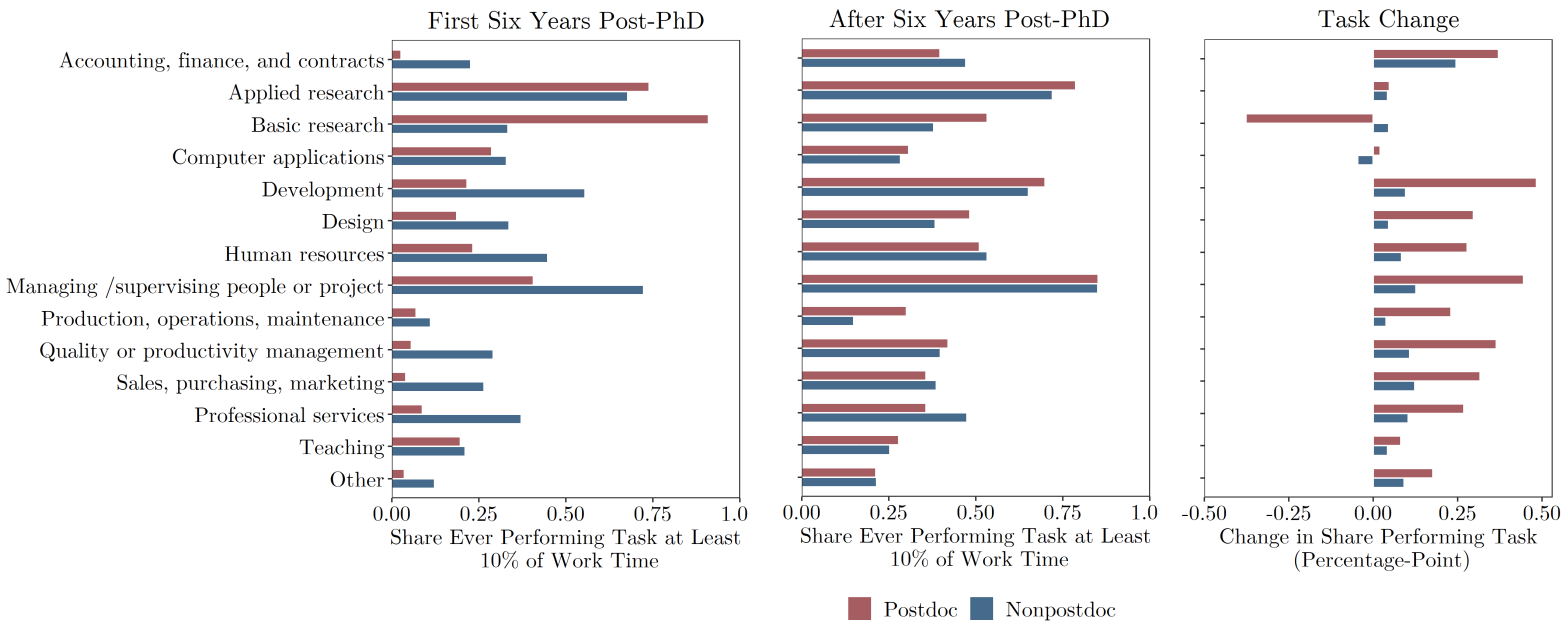
Figures and Tables

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



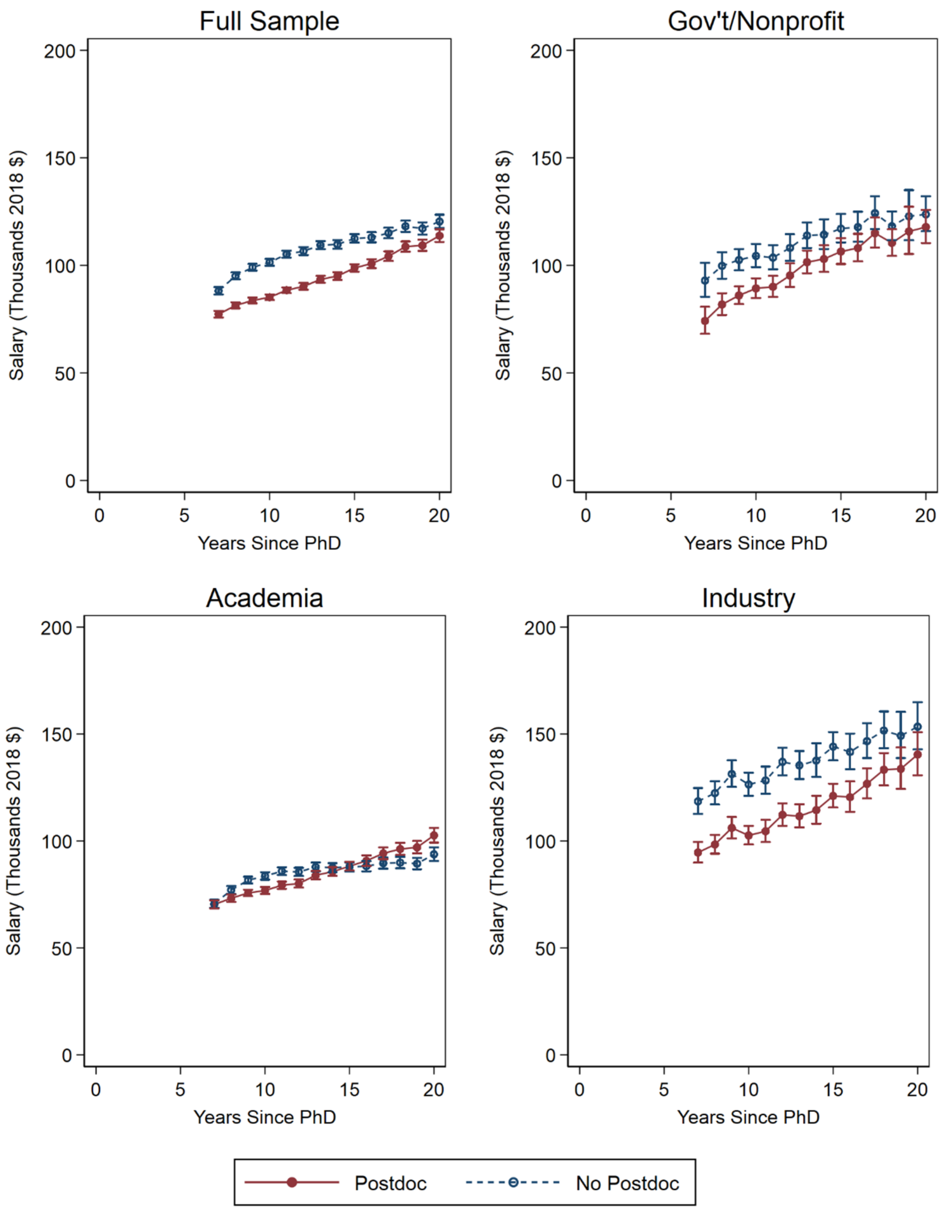
Notes: Figure 1 shows the median salary in each 3-year interval since PhD for biomedical doctorates first appearing in the SDR 1993, 1995, or 1997 waves and who graduated no earlier than 1990. Biomedical doctorates are associated with the employment sector (academia or industry) that they occupy at 10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

Figure 2: Change in Tasks for Postdocs and Nonpostdocs Working in Industry



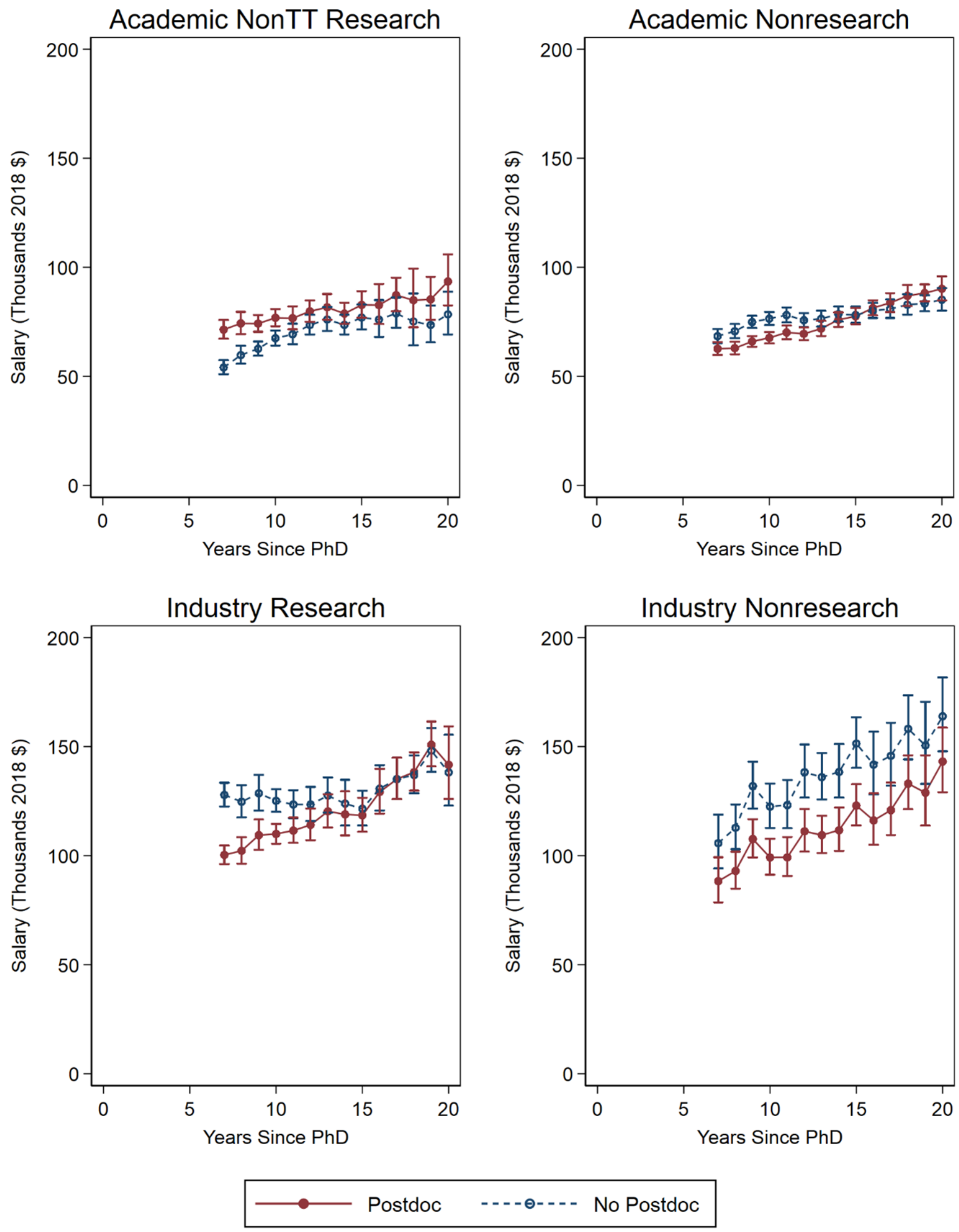
Notes: Figure 2 gives the change in the share of postdocs and nonpostdoc performing tasks for at least 10% of work time among biomedical doctorates working in industry. The tasks performed by postdocs in their first six years represent the tasks performed as part of postdoc training. Greater magnitudes of task change represent greater degrees of mismatch in a given task. See Table A.3 for the underlying data used to construct this figure.

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 specification 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 with 95% confidence intervals 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 specifications used to generate the predictions. Salary adjusted for inflation using the CPI-U.

Figure 4: Average Predicted After-Postdoc Salary Over Career by Postdoc-Trained Status and Subsector: Postdoc Training as Experience, 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 specification found in Column (4) of Table 5 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 with 95% confidence intervals 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 specifications used to generate the predictions. Salary adjusted for inflation using the CPI-U.

Table 1: Analytical Sample Observations by Employment Sector

Employment Sector:	In Sector at 10 years post-PhD			In Sector in Year of Observation†		
Group:	Postdoc	Non-Postdoc	Total	Postdoc	Non-Postdoc	Total
Panel A: Number of Observations (Person-Count)						
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)
Panel B: Person Share: Row (Column) [Cell]						
All Sectors	0.72 (1.00) [0.72]	0.28 (1.00) [0.28]	1.00 (1.00) [1.00]	0.72 (1.00) [0.72]	0.28 (1.00) [0.28]	1.00 (1.00) [1.00]
Academia	0.77 (0.57) [0.41]	0.23 (0.44) [0.12]	1.00 (0.53) [0.53]	0.76 (0.64) [0.46]	0.24 (0.50) [0.14]	1.00 (0.60) [0.60]
TT Research	0.91 (0.23) [0.17]	0.09 (0.06) [0.02]	1.00 (0.18) [0.18]	0.89 (0.32) [0.23]	0.11 (0.10) [0.03]	1.00 (0.26) [0.26]
Non-TT Research	0.83 (0.12) [0.08]	0.17 (0.06) [0.02]	1.00 (0.10) [0.10]	0.82 (0.20) [0.14]	0.18 (0.11) [0.03]	1.00 (0.17) [0.17]
Nonresearch	0.64 (0.23) [0.16]	0.36 (0.32) [0.32]	1.00 (0.25) [0.25]	0.70 (0.39) [0.28]	0.30 (0.42) [0.12]	1.00 (0.40) [0.40]
Industry	0.65 (0.28) [0.20]	0.35 (0.37) [0.11]	1.00 (0.31) [0.31]	0.67 (0.35) [0.25]	0.33 (0.44) [0.12]	1.00 (0.37) [0.37]
Research	0.73 (0.15) [0.11]	0.27 (0.14) [0.04]	1.00 (0.15) [0.15]	0.73 (0.24) [0.17]	0.27 (0.22) [0.06]	1.00 (0.23) [0.23]
Nonresearch	0.58 (0.13) [0.09]	0.42 (0.23) [0.06]	1.00 (0.16) [0.16]	0.63 (0.24) [0.17]	0.37 (0.35) [0.10]	1.00 (0.27) [0.27]
Gov't/Nonprofits	0.66 (0.15) [0.10]	0.34 (0.19) [0.05]	1.00 (0.16) [0.16]	0.69 (0.24) [0.17]	0.31 (0.27) [0.08]	1.00 (0.24) [0.24]
Panel C: Share of Workers Ever in Sector Who are in Sector at Ten Years Post-PhD						
Academia	0.89	0.88	0.89	...	...	...
TT Research	0.71	0.61	0.70	...	...	...
Non-TT Research	0.59	0.55	0.58	...	...	...
Nonresearch	0.59	0.75	0.64	...	...	...
Industry	0.81	0.85	0.82	...	...	...
Research	0.65	0.64	0.65	...	...	...
Nonresearch	0.54	0.67	0.59	...	...	...
Gov't/Nonprofits	0.62	0.72	0.65	...	...	...

Notes: Panel A 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. Panel B gives the row, column, and total share of persons in each cell as calculated from Panel A. Panel C lists the share of workers ever in a given sector who are observed in that sector at 10 years post-PhD—calculated by dividing the person counts in the first three columns by the respective values in the last three columns. † = 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

Employment Sector:	Full Sample		Academia		Industry		Gov't/Nonprofit	
Group:	Postdoc	Nonpostdoc	Postdoc	Nonpostdoc	Postdoc	Nonpostdoc	Postdoc	Nonpostdoc
Foreign-born	0.25	0.20	0.25	0.17	0.27	0.22	0.23	0.17
Temp. Resident	0.13	0.07	0.13	0.06	0.14	0.09	0.10	0.06
Age at PhD	30.47	32.69	30.53	33.19	30.26	31.55	30.75	33.26
Female	0.39	0.38	0.39	0.40	0.39	0.36	0.40	0.36
Asian	0.18	0.13	0.17	0.10	0.21	0.17	0.17	0.10
Minority	0.08	0.10	0.08	0.09	0.06	0.11	0.17	0.10
PhD Length	6.69	7.75	6.77	7.97	6.57	7.45	6.81	7.96
Married at PhD	0.53	0.63	0.55	0.66	0.53	0.60	0.51	0.59
Child at PhD	0.30	0.45	0.32	0.47	0.28	0.41	0.30	0.40
Fellowship during PhD	0.17	0.17	0.17	0.17	0.15	0.15	0.19	0.15
RA during PhD	0.31	0.23	0.30	0.21	0.33	0.27	0.30	0.22
TA during PhD	0.12	0.14	0.12	0.16	0.11	0.10	0.11	0.15
Mother's Highest Education: BA	0.22	0.20	0.22	0.19	0.22	0.20	0.21	0.19
Mother's Highest Education: $>$ BA	0.19	0.16	0.20	0.16	0.18	0.18	0.21	0.19
Father's Highest Education: BA	0.23	0.21	0.24	0.20	0.22	0.21	0.20	0.24
Father's Highest Education: $>$ BA	0.34	0.30	0.34	0.30	0.32	0.30	0.35	0.27
N	3420	1358	2192	674	1193	593	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. A given doctorate who switches employment sectors during their career will appear in multiple employment sector samples to be consistent with the samples underlying the results in columns (3) through (6) of Table 3.

Table 3: Postdoc Salary Premium by Employment Sector

Dependent Variable: log(salary)	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All Sectors	N = 29598		N = 22512		N = 26312	
Postdoc Training	-0.115***	-0.138***	-0.0842***	-0.117***	0.0253	0.000956
	(0.0202)	(0.0201)	(0.0236)	(0.0235)	(0.0209)	(0.0210)
R^2	0.181	0.272	0.130	0.246	0.143	0.244
Panel B. Academia	N = 16067		N = 11941		N = 13947	
Postdoc Training	-0.0201	-0.0602**	0.0318	-0.00836	0.126***	0.0983***
	(0.0256)	(0.0277)	(0.0307)	(0.0337)	(0.0270)	(0.0294)
R^2	0.232	0.363	0.159	0.314	0.159	0.301
Panel C. Industry	N = 8799		N = 6708		N = 7898	
Postdoc Training	-0.138***	-0.213***	-0.103**	-0.158***	-0.0102	-0.0450
	(0.0377)	(0.0376)	(0.0423)	(0.0410)	(0.0380)	(0.0385)
R^2	0.176	0.381	0.132	0.400	0.141	0.376
Panel D. Gov't/Nonprofit	N = 4732		N = 3863		N = 4467	
Postdoc Training	-0.135***	0.00392	-0.0867**	-0.106**	0.0318	0.0177
	(0.0404)	(0.0542)	(0.0349)	(0.0450)	(0.0322)	(0.0396)
R^2	0.201	0.409	0.201	0.540	0.224	0.528
Observations during postdoc included?:						
Yes	✓	✓				
No			✓	✓	✓	✓
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. Columns (1) and (2) report results where we include all person-year observations, including those associated with years when a doctorate is employed as a postdoc, and where employment sector is defined as that observed at 10 years post-PhD. In columns (3) through (6), we keep only those person-year observations corresponding to years after any and all years employed as a postdoc and associate each observation with the employment sector observed for each doctorate in the given year (i.e., the "current" employment sector). In columns (1) through (4), experience is measured as years since PhD graduation for all biomedical doctorates (i.e., years in postdoc training are treated as contributing to experience). In columns (5) and (6), 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)—this is akin to treating postdoctoral training as schooling rather than experience. For columns (3) and (4), we drop all observations within the first six years after Ph.D. so that postdoc and nonpostdoc observations are comparable. In specifications (5) and (6), 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 postdoc training is treated as schooling. 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.5. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Postdoc Training and the Likelihood of a Research Job

	Any	Academic	Tenure-Track	Tenured	Industry
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 research 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. Robust standard errors clustered at the field-cohort level are in parentheses. Specifications include all controls listed in Table A.5.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Postdoc Salary Premium by Employment Subsector

Dependent Variable: log(salary)	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Academic TT Research	$N = 5621$		$N = 3996$		$N = 4394$	
Postdoc Training	-0.176***	-0.381***	-0.0941*	-0.174***	0.00601	-0.0500
	(0.0515)	(0.0409)	(0.0495)	(0.0557)	(0.0455)	(0.0533)
R^2	0.358	0.56	0.168	0.349	0.169	0.349
Panel B. Academic NonTT Research	$N = 2916$		$N = 1988$		$N = 2408$	
Postdoc Training	-0.102*	-0.130	-0.0244	0.159**	0.115**	0.232***
	(0.0591)	(0.130)	(0.0584)	(0.0788)	(0.0541)	(0.0678)
R^2	0.242	0.491	0.189	0.531	0.165	0.498
Panel C. Academic Nonresearch	$N = 7530$		$N = 5957$		$N = 7145$	
Postdoc Training	-0.0253	0.0114	0.00369	-0.0416	0.0812**	0.0481
	(0.0333)	(0.0399)	(0.0396)	(0.0476)	(0.0346)	(0.0397)
R^2	0.208	0.445	0.189	0.453	0.174	0.419
Panel D. Industry Research	$N = 4300$		$N = 3117$		$N = 3801$	
Postdoc Training	-0.101*	-0.176***	-0.00865	-0.0832*	0.0714*	0.0162
	(0.0540)	(0.0598)	(0.0490)	(0.0446)	(0.0430)	(0.0440)
R^2	0.183	0.390	0.138	0.482	0.149	0.453
Panel E. Industry Nonresearch	$N = 4499$		$N = 3591$		$N = 4097$	
Postdoc Training	-0.153***	-0.207***	-0.160***	-0.155***	-0.0701	-0.0707
	(0.0499)	(0.0644)	(0.0570)	(0.0762)	(0.0520)	(0.0722)
R^2	0.221	0.522	0.177	0.499	0.180	0.473
Observations during postdoc included?:						
Yes	✓	✓				
No			✓	✓	✓	✓
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. Columns (1) and (2) report results where we include all person-year observations, including those associated with years when a doctorate is employed as a postdoc, and where employment subsector is defined as that observed at 10 years post-PhD. In columns (3) through (6), we keep only those person-year observations corresponding to years after any and all years employed as a postdoc and associate each observation with the employment subsector observed for each doctorate in the given year (i.e., the "current" employment subsector). In columns (1) through (4), experience is measured as years since PhD graduation for all biomedical doctorates (i.e., years in postdoc training are treated as contributing to experience). In columns (5) and (6), 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)—this is akin to treating postdoctoral training as schooling rather than experience. For columns (3) and (4), we drop all observations within the first six years after Ph.D. so that postdoc and nonpostdoc observations are comparable. In specifications (5) and (6), 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 postdoc training is treated as schooling. 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.5. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Controlling for Task History and Current Tasks in Industry Salary Regressions

Dependent Variable: log(salary)	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Task History Controls			$N = 3104$			
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
Panel B: Current Job Task Controls			$N = 3104$			
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						
Included Task Control Sets						
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. 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. In Panel A, we add controls for the history of tasks performed as part of previous employment. In Panel B, we add controls for the tasks associated with the current job. 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.5. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Task Mismatch and 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***	0.0581
		(0.0509)	(0.120)		(0.0671)	(0.126)
Task Distance			-0.309***			-0.435***
			(0.109)			(0.113)
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***	-0.357*
		(0.107)	(0.246)		(0.123)	(0.200)
Task Distance			-0.0577			0.0140
			(0.226)			(0.165)
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.5. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix

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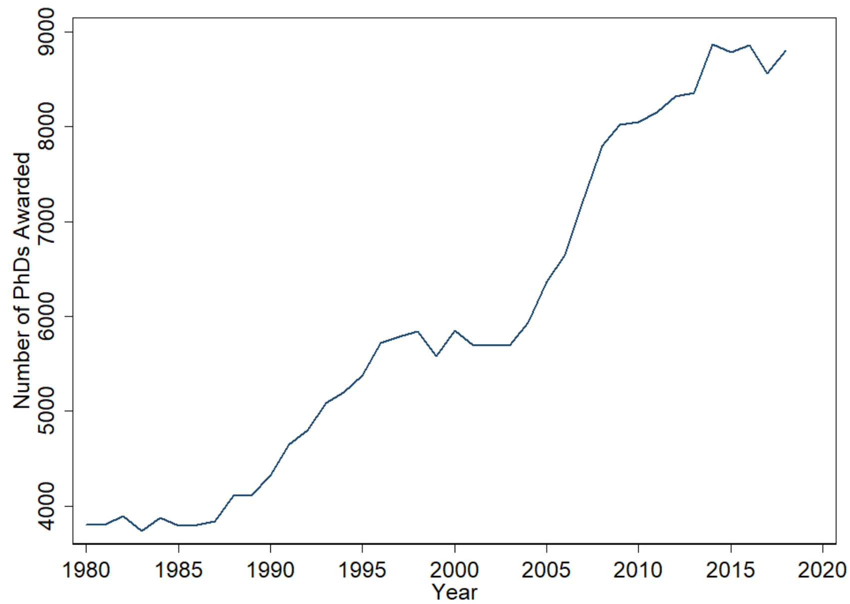
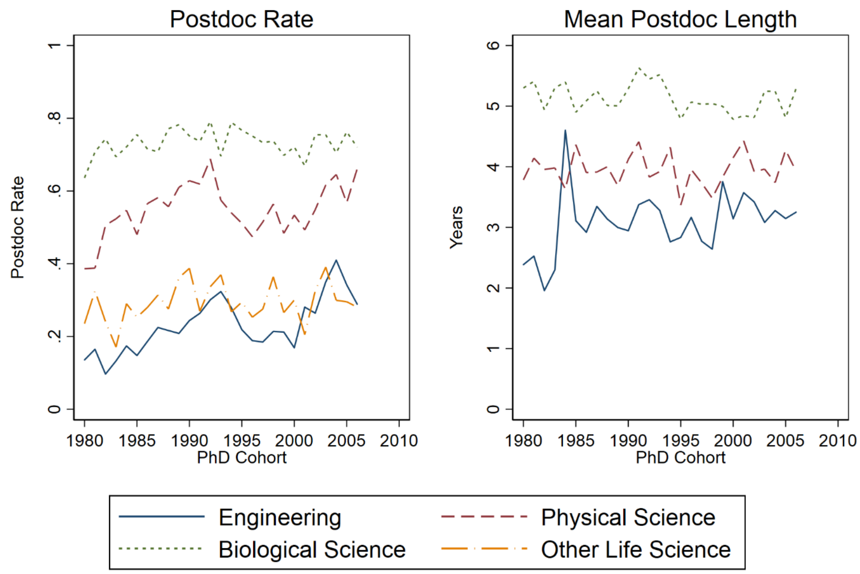
A Supplementary Figures and Tables

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



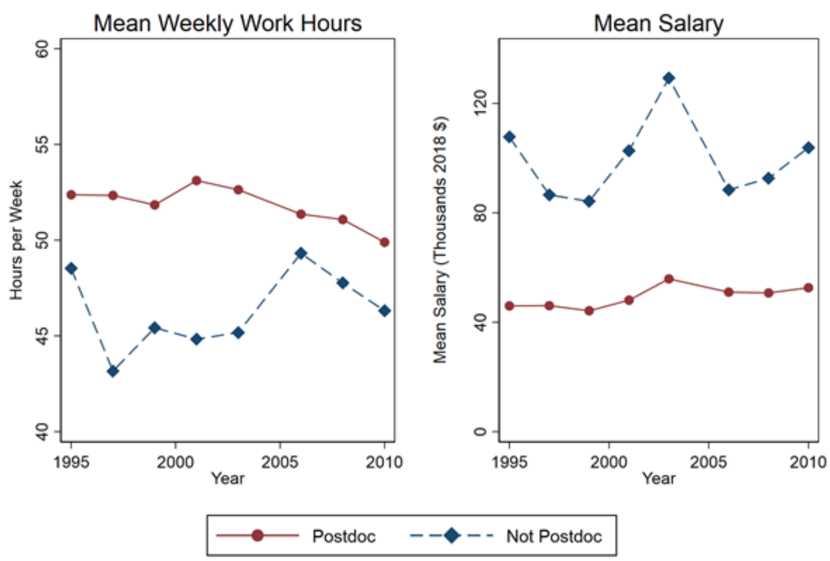
Notes: Figure A.1 shows the number of PhDs awarded in Biological and Biomedical Sciences in each year. Data is from the NSF's Survey of Earned Doctorates (SED).

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



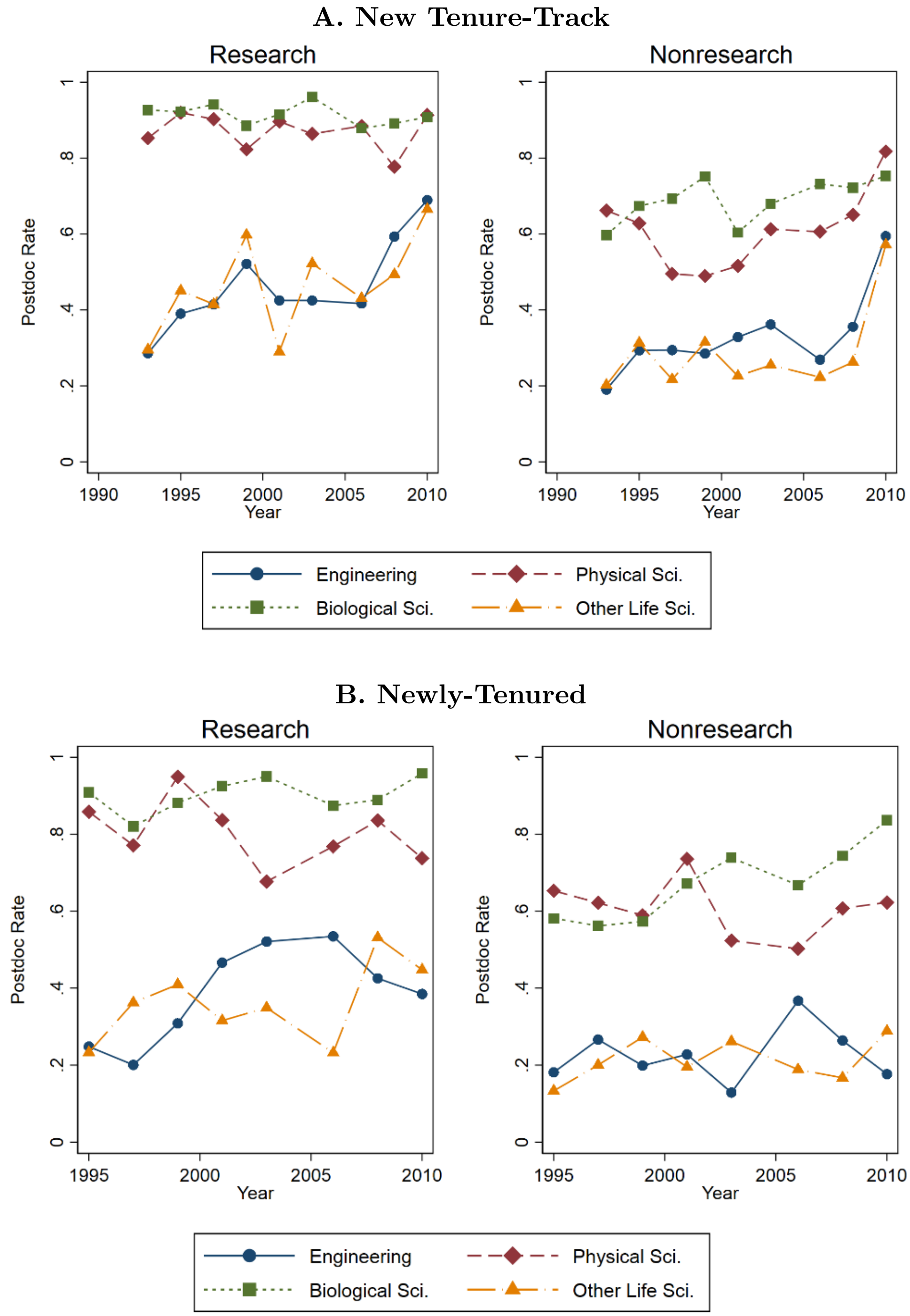
Notes: The left panel of Figure A.2 shows the proportion of doctorates in each PhD cohort that ever take a postdoc by broad field of study. The right panel show the mean length of postdoc training for all postdoc-trained PhD cohort members by broad field of study. Sample restricted to doctorates appearing 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



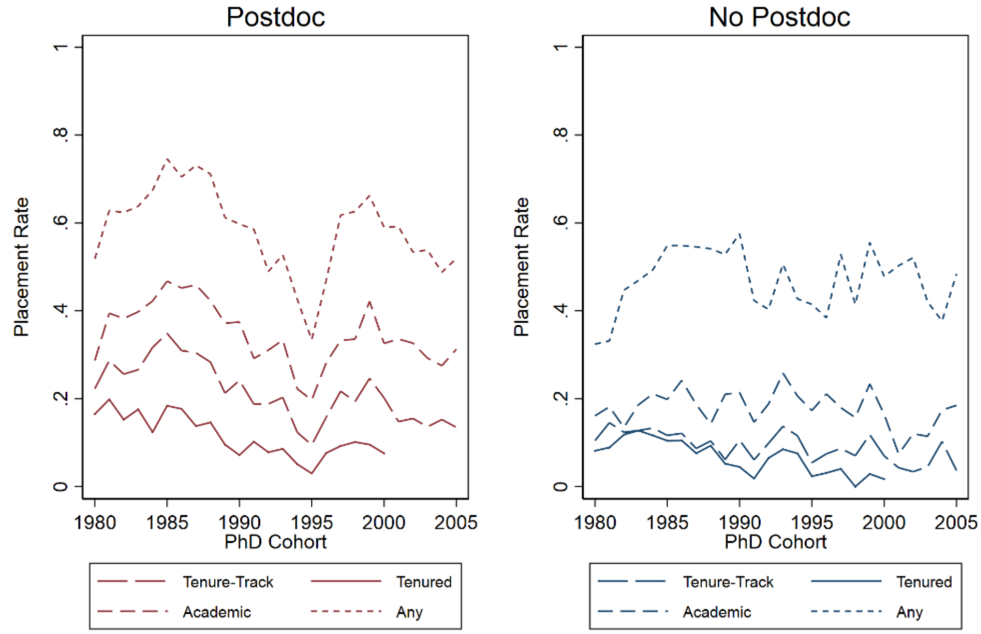
Notes: Figure A.3 shows the average work hours and salary for biomedical doctorates age 28-32 employed as postdocs in the given year compared to biomedical doctorates of the same age employed in industry in the same year. Sample restricted to doctorates appearing in the NSF's Survey of Doctorate Recipients 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.

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



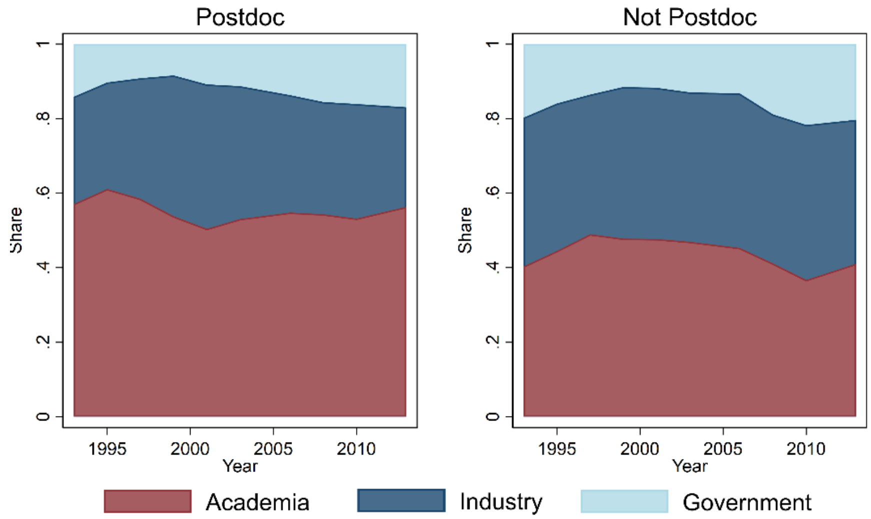
Notes: Figure A.4 shows the postdoc-share of individuals who first report being employed in a tenure-track position (Panel A) or tenured position (Panel B) in a given SDR wave by broad field of study. Sample restricted to doctorates appearing in the NSF's Survey of Doctorate Recipients in any wave(s) 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: Research Job Placement Rates by Prior Postdoc Status



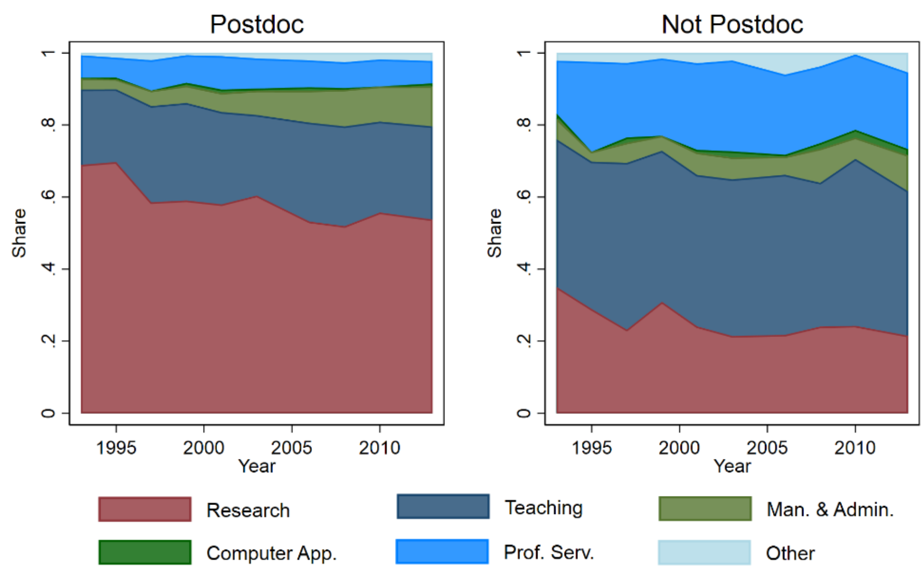
Notes: Figure A.5 shows proportion of biomedical doctorates who take the indicated academic research position (excluding postdoc positions) within 15 years post-PhD by PhD cohort and whether individual has postdoc training. We require that we observe an individual for the full 15 years post-PhD for "Tenured" 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.6: Share of Biomedical Doctorates Working in Each Employment Sector



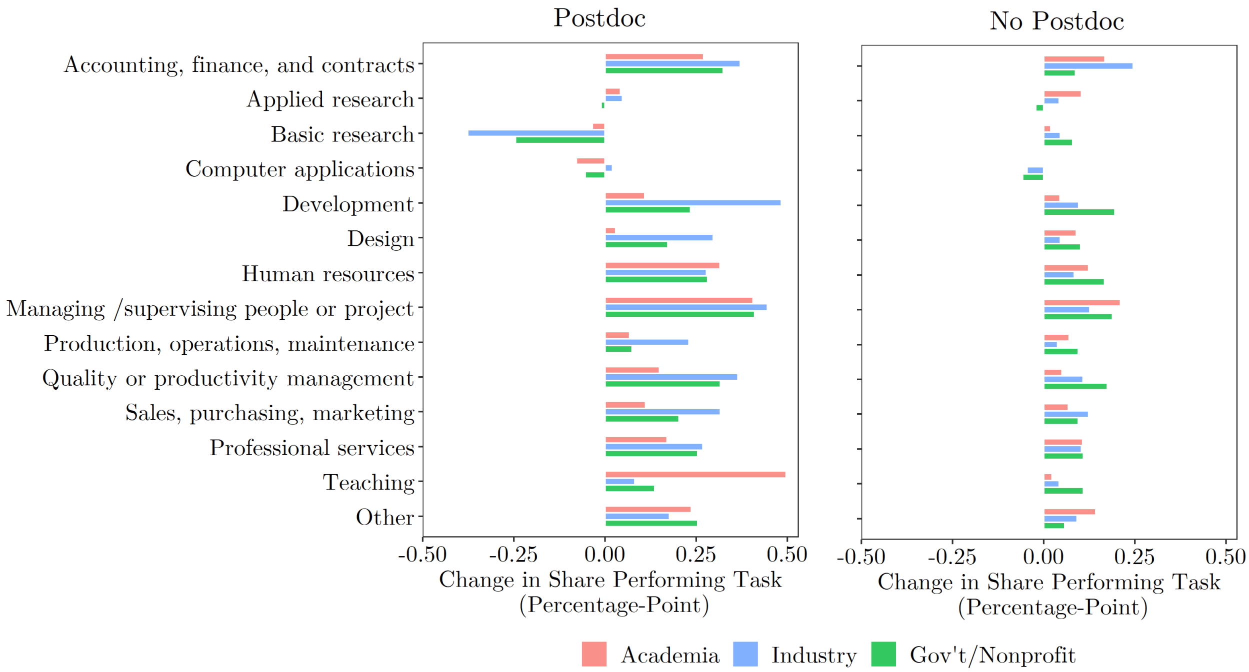
Notes: Figure A.6 shows the share of biomedical doctorates age 30 to 40 working in each employment sector by year and whether they have previous postdoc training; those employed as postdocs in the given year are excluded. "Government" sector includes both government and nonprofits. Sample restricted 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.7: Share of Biomedical Doctorates in Academia by Primary Work Activity



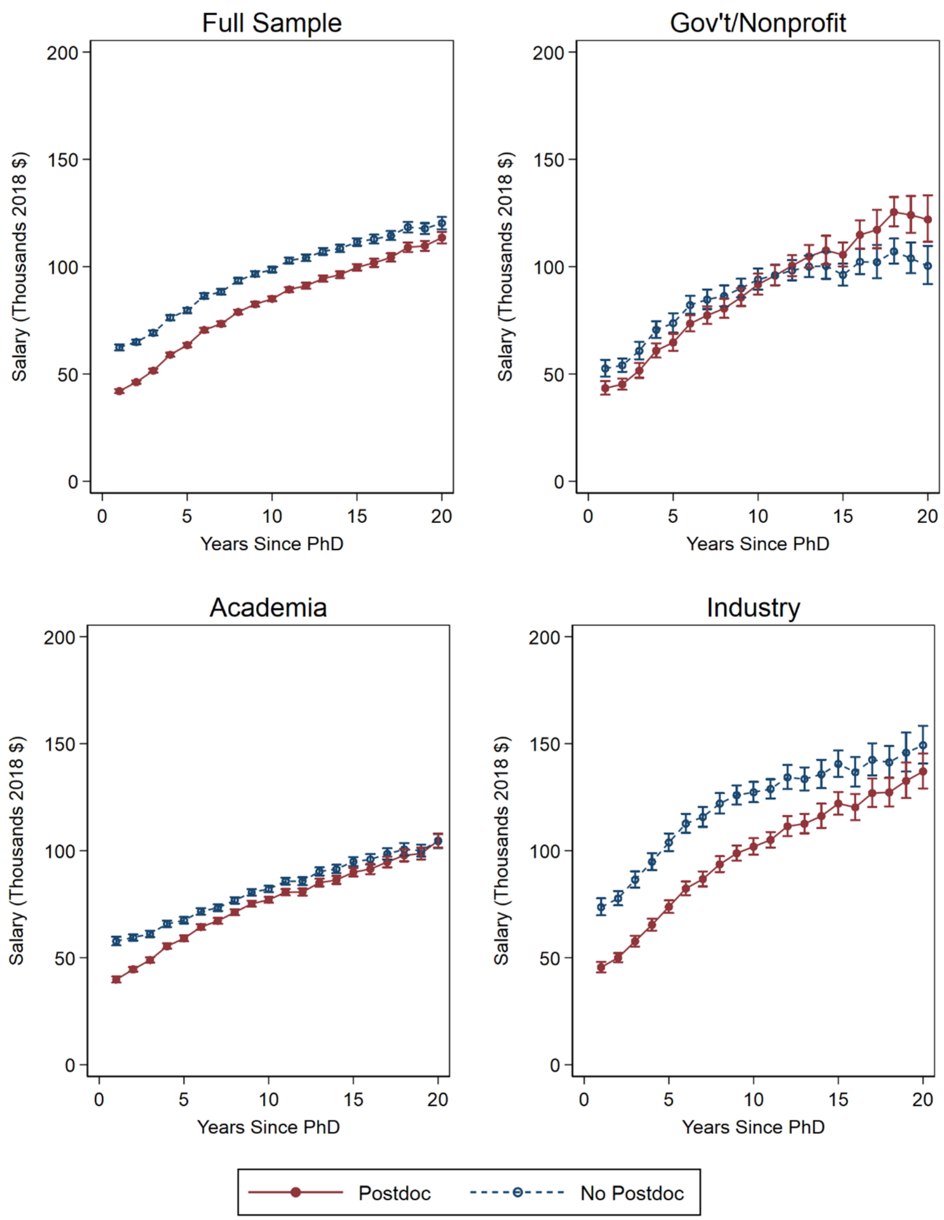
Notes: Figure A.7 shows the share of academia-employed biomedical doctorates age 30 to 40 in different reported primary job tasks by year and whether they have postdoc training; those employed as postdocs in the given year are excluded. Sample restricted to doctorates appearing in the NSF's Survey of 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.

Figure A.8: Change in Tasks for Postdocs and Nonpostdocs By Sector



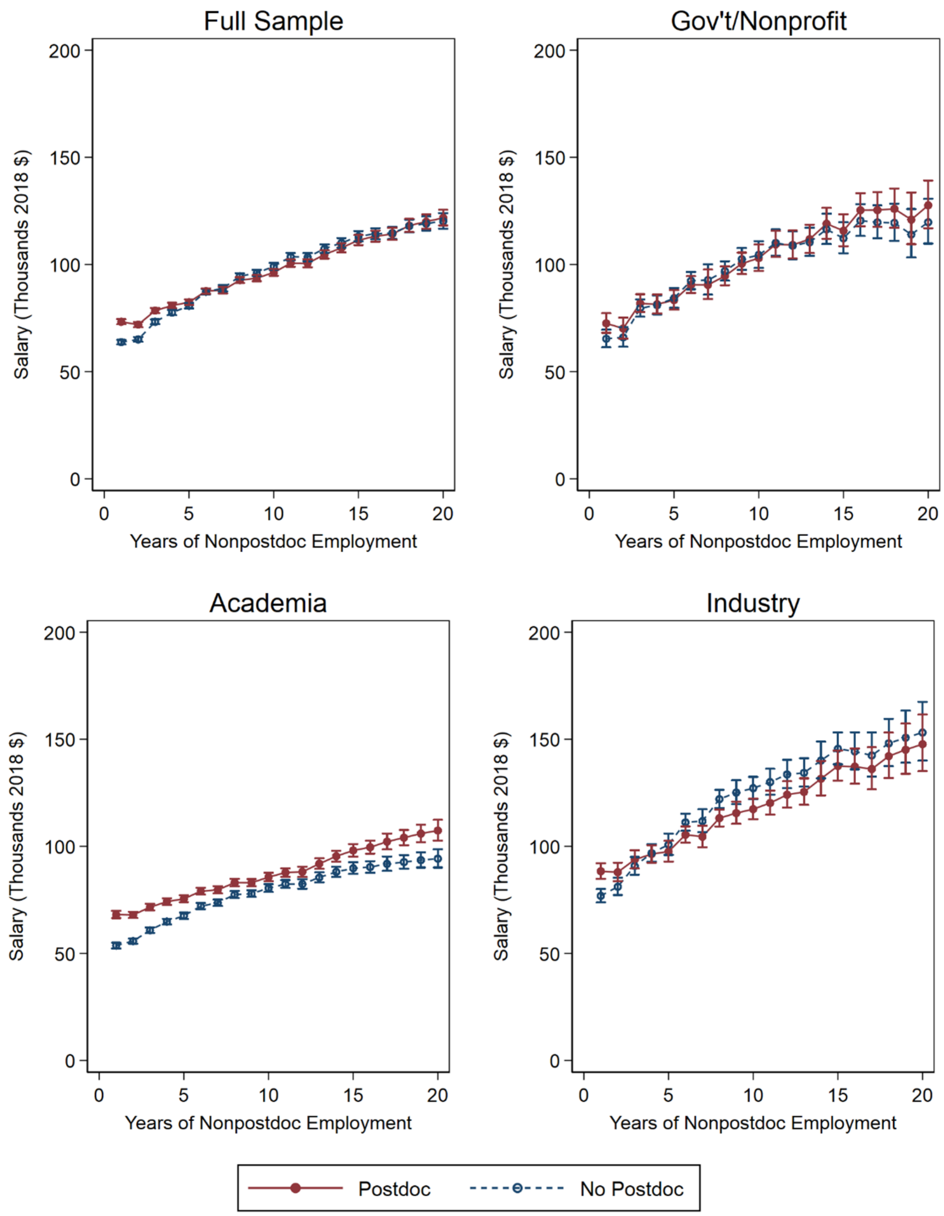
Notes: Figure A.8 gives the change in the share of postdocs and nonpostdoc performing tasks for at least 10% of work time among biomedical doctorates working in each sector. Greater magnitudes of task change represent greater degrees of mismatch in a given task. See Table A.3 and Table A.4 for the underlying data used to construct this figure.

Figure A.9: Average Predicted Salary Over Career by Postdoc-Trained Status: Postdoc Training as Experience, Postdoc Salary Observations Included



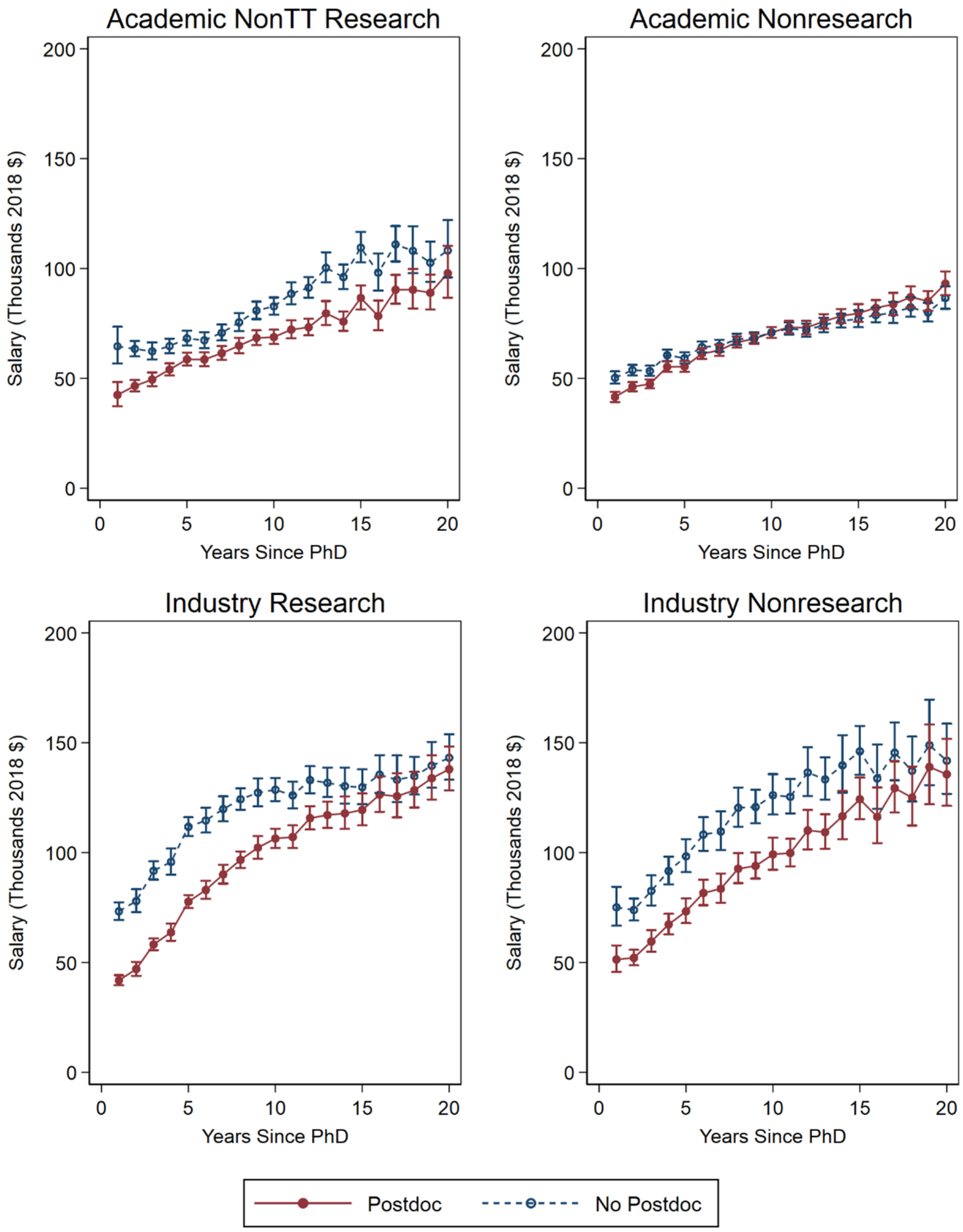
Notes: Figure A.9 shows the average of predicted salary profiles for biomedical doctorates with and without postdoc training generated by an augmented version of the specification found in Column (2) of Table 3 where we allow for interactions between the indicator variable for postdoc training and quartic 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 with 95% confidence intervals in Figure A.9. Salary adjusted for inflation using the CPI-U.

Figure A.10: Average Predicted After-Postdoc Salary Over Career by Postdoc-Trained Status: Postdoc Training as Schooling, Postdoc Salary Observations Excluded



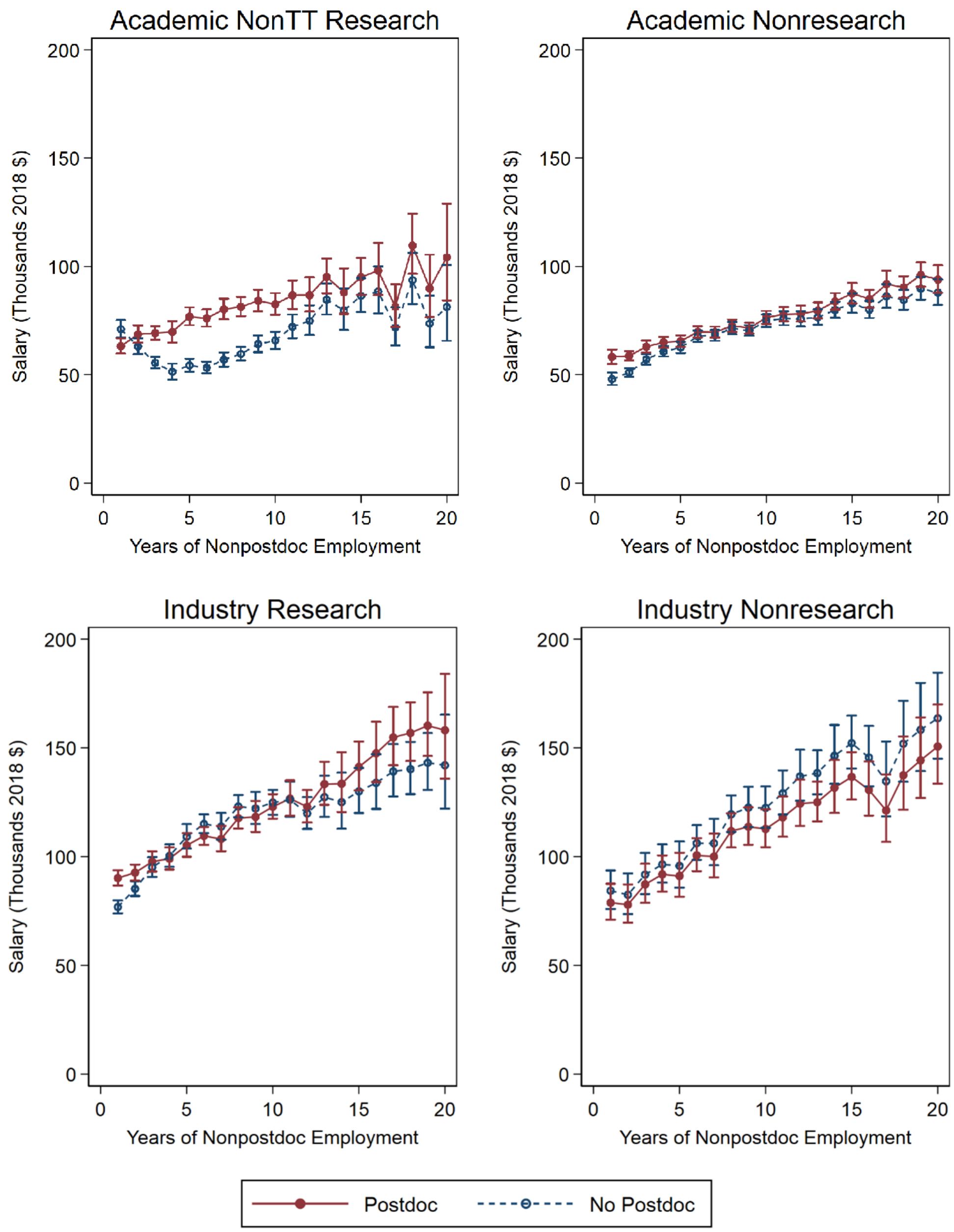
Notes: Figure A.10 shows the average of predicted salary profiles for biomedical doctorates with and without postdoc training generated by an augmented version of the specification found in Column (6) of Table 3 where we allow for interactions between the indicator variable for postdoc training and quartic 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 with 95% confidence intervals in Figure A.10. 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 specifications used to generate the predictions. Salary adjusted for inflation using the CPI-U.

Figure A.11: Average Predicted Salary Over Career by Postdoc-Trained Status and Subsector: Postdoc Training as Experience, Postdoc Salary Observations Included



Notes: Figure A.11 shows the average of predicted salary profiles for biomedical doctorates with and without postdoc training generated by an augmented version of the specification found in Column (2) of Table 5 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 with 95% confidence intervals in Figure A.11. The employment sector subsamples are based on each doctorate's sector of employment at ten years post-PhD. Salary adjusted for inflation using the CPI-U.

Figure A.12: Average Predicted After-Postdoc Salary Over Career by Postdoc-Trained Status and Subsector: Postdoc Training as Schooling, Postdoc Salary Observations Excluded



Notes: Figure A.12 shows the average of predicted salary profiles for biomedical doctorates with and without postdoc training generated by an augmented version of the specification found in Column (6) of Table 5 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 with 95% confidence intervals in Figure A.12. 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 specifications used to generate the predictions. Salary adjusted for inflation using the CPI-U.

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

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

Notes: This table lists the biomedical fields represented in our analytical sample.

Table A.2: 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	
Group:	No Pdoc	Pdoc	No Pdoc	Pdoc	No Pdoc	Pdoc	No Pdoc	Pdoc	No Pdoc	Pdoc	No Pdoc	Pdoc
Acct., Finance, and Contracts	–	–	–	1.50%	–	–	4.21%	4.21%	–	–	–	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	–	–	–	1.20%	6.90%	2.00%	7.28%	6.21%	–	–	–	–
Development	–	–	–	1.70%	18.39%	–	27.59%	25.85%	–	–	10.14%	8.59%
Design	–	–	–	–	–	–	–	4.61%	–	–	–	–
Human Resources	–	–	3.36%	1.00%	–	–	–	–	–	–	–	–
Managing People or Projects	8.40%	1.20%	21.29%	23.48%	19.16%	–	38.70%	37.27%	23.19%	–	49.28%	40.23%
Production, Operations, Maint.	–	–	–	–	–	–	–	3.81%	–	–	–	–
Quality or Productivity Mgmt.	–	–	–	–	–	–	4.60%	5.81%	–	–	–	–
Sales, Purchasing, Marketing	–	–	–	–	4.98%	–	8.05%	8.82%	–	–	–	–
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%	–	–	–	–	–	–	–	–
Other	3.08%	1.30%	7.56%	3.70%	7.28%	–	10.34%	9.02%	15.22%	–	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. "–" reported in cells of insufficient size to be disclosed. N reports person counts.

Table A.3: 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	
Group:	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 A.4: 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	
Group:	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.5: 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.6: 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.6 reports coefficient estimates of a LPM regression of an indicator variable for if a doctorate ever is employed as a postdoc on our salary regression controls. Observations are person level. Robust standard errors clustered on field-cohort in parentheses. See Table A.5 for the definition of each covariate. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: Postdoc Training and the Likelihood of an Academic Job

	Academic (Any)	Tenure-Track	Tenured
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
Fixed Effects			
Field-Cohort	✓	✓	✓
PhD University	✓	✓	✓

Notes: See notes to Table 4. 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 which, unlike Table 4, are not restricted to research-focused jobs.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: Task Regression Sample Observations by Employment Sector

Employment Sector	In Sector in Year of Observation†		
	Postdoc	Non-Postdoc	Total
Panel A: Number of Observations (Person-Count)			
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)
Panel B: Person Share: Row (Column) [Cell]			
All Sectors	0.73 (1.00) [0.73]	0.27 (1.00) [0.27]	1.00 (1.00) [1.00]
Academia	0.77 (0.63) [0.46]	0.23 (0.49) [0.13]	1.00 (0.59) [0.59]
TT Research	0.90 (0.28) [0.21]	0.10 (0.09) [0.02]	1.00 (0.23) [0.23]
Non-TT Research	0.83 (0.20) [0.14]	0.13 (0.11) [0.03]	1.00 (0.17) [0.17]
Nonresearch	0.71 (0.38) [0.28]	0.29 (0.42) [0.11]	1.00 (0.39) [0.39]
Industry	0.70 (0.35) [0.26]	0.30 (0.40) [0.11]	1.00 (0.37) [0.37]
Research	0.75 (0.23) [0.17]	0.25 (0.20) [0.06]	1.00 (0.22) [0.22]
Nonresearch	0.67 (0.24) [0.18]	0.33 (0.31) [0.09]	1.00 (0.26) [0.26]
Gov't/Nonprofits	0.72 (0.23) [0.17]	0.28 (0.24) [0.07]	1.00 (0.23) [0.23]

Notes: 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. Panel A lists the number of observations (and unique individuals) in each employment sector for the task regression sample by whether each observation is associated with a biomedical doctorate with postdoctoral training. Panel B gives the row, column, and total share of persons in each cell as calculated from Panel A. † = 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 exceeds the total number of persons included in the analytical sample.

Table A.9: Controlling for Task History and Current Tasks in Salary Regressions

Dependent Variable: log(salary)	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Task History Controls						
I. All Sectors			$N = 10215$			
Postdoc Training	-0.117***	-0.0716**	-0.0582*	-0.0748*	-0.0665**	-0.0696**
	(0.0321)	(0.0312)	(0.0310)	(0.0317)	(0.0308)	(0.0312)
R^2	0.301	0.343	0.346	0.346	0.354	0.362
II. Academia			$N = 5442$			
Postdoc Training	-0.0185	-0.0265	-0.0228	-0.0361	-0.0347	-0.0361
	(0.0415)	(0.0385)	(0.0372)	(0.0387)	(0.0374)	(0.0373)
R^2	0.422	0.463	0.470	0.469	0.481	0.486
III. Gov't/Nonprofit			$N = 1669$			
Postdoc Training	-0.103	0.00563	-0.0256	-0.0788	-0.0917	-0.0228
	(0.0789)	(0.0821)	(0.0854)	(0.0862)	(0.0641)	(0.0915)
R^2	0.703	0.722	0.714	0.717	0.724	0.733
Panel B: Current Job Task Controls						
I. All Sectors			$N = 10215$			
Postdoc Training	-0.117***	-0.100***	-0.0898***	-0.119***	-0.103***	-0.114***
	(0.0321)	(0.0303)	(0.0300)	(0.0309)	(0.0300)	(0.0300)
R^2	0.301	0.348	0.348	0.339	0.355	0.363
II. Academia			$N = 5442$			
Postdoc Training	-0.0185	-0.0313	-0.0361	-0.0711*	-0.0653*	-0.0722*
	(0.0415)	(0.0388)	(0.0373)	(0.0383)	(0.0367)	(0.0368)
R^2	0.422	0.455	0.462	0.459	0.475	0.479
III. Gov't/Nonprofit			$N = 1669$			
Postdoc Training	-0.103	-0.0698	-0.0741	-0.0400	-0.0274	-0.0280
	(0.0789)	(0.0811)	(0.0767)	(0.0930)	(0.0859)	(0.0916)
R^2	0.703	0.712	0.709	0.709	0.716	0.718
Postdoc Training Treated As:						
Experience	✓	✓	✓	✓	✓	✓
Schooling						
Included Task Control Sets						
Primary Activity		✓				✓
Primary or Secondary Activity			✓		✓	
Activity $\geq$ 10% of Work Time				✓	✓	✓

Notes: See Table 6 for industry sector results. 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. 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. In Panel A, we add controls for the history of tasks performed as part of previous employment. In Panel B, we add controls for the tasks associated with the current job. 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.5. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.10: 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.5. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.11: 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.6 reports coefficient estimates on the (primary) task history controls included in the regression whose main results are report in Panel A column (2) of Table 6. Applied research is the base case and so estimates yield the 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 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 "postdoc." 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.[68]

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.[69] 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 since PhD graduation.[70]

[68]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.

[69]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.

[70]In the analytical sample used in this study, we find that 77% of postdoc person-years occur in academia, 17%

C Bias-Adjusted Estimates of the Effect of Postdoc Training

C.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.[71] 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.[72]

C.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 (4) of Table 3 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.[73] 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'

occur in government/nonprofits, and only 6% occur in industry.

[71] 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.

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

[73] 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.[74]

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 C.1 (and Table C.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 positive direction for all sectors in Table C.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.[75] 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 C.1 and Table C.2.

We find that each point estimate in Panel A of Table C.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 (4) of Table 3 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.[76] Altogether, these results suggest that ability bias is unlikely to explain the

[74]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.

[75]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).

[76]The calculated upper-bounds all lie outside the 95% confidence interval of the corresponding estimate in column (4) of Table 3, 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 C.1 and Table C.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 C.1 and Table C.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.

C.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 Table 4 to selection on unobservables using the Oster's (2019) method as before and report the results in Table C.3. We find that the results in Table 4 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 C.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 4, indicating that the results are not especially sensitive to selection on unobservables.[77]

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 led to the accumulation of task-specific human capital (which is the focus of Section 6).

[77]We use the standard errors reported in Table 4. 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

Table C.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 (4) and (6) of Table 3 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 3. 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.

fact that inclusion of the observable controls increases the R^2 drastically relative to the uncontrolled regression.

Table C.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		$0.611^{\dagger}$		0.589		0.626		0.649	
$\theta*$	-0.339		$0.546^{\dagger}$		-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		$0.572^{\dagger}$		0.544		0.589		0.615	
$\theta*$	0.00102		$0.573^{\dagger}$		0.0316		0.0519		-0.0756	
N	4394		2408		7145		3801		4097	

Notes: We test if the results in columns (4) and (6) of Table 5 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 5. 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 C.3: Sensitivity of Research Job Regression Results to Selection on Unobservables

Research Job Type:	Any		Academic		Tenure-Track		Tenured		Industry	
	$\hat{\theta}$	R^2	$\hat{\theta}$	R^2	$\hat{\theta}$	R^2	$\hat{\theta}$	R^2	$\hat{\theta}$	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
R_{max}	0.384		0.349		0.342		0.884		0.640	
$\theta*$	0.231		0.271		0.202		-1.47		0.090	
N	4778		4778		4778		798		1786	

Notes: We test if the results in Panel B of Table 4 are robust to allowing for selection on unobservables using the methods developed in Oster (2019); see notes to Table 4. 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.

D Does Postdoc Spell Duration Matter?

The results reported in column (4) of Table 3 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 the longest—to suffer the largest after-postdoc salary penalties. To test this, we repeat the analysis in Table 3 after replacing the single indicator variable for if a biomedical doctorate is postdoc-trained with three indicator variables based on whether a doctorate participated in postdoc training for 1) no longer than three years, 2) greater than three years but less than six years, and 3) exceeding six years. Table D.1 reports the results. We first focus attention to specification (4) 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 (6) 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.[78]

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 4 after replacing the single indicator variable for if a biomedical doctorate is postdoc-trained with the three indicator variables based on postdoc length. Panel B of Table D.2 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.

[78] Andalib, Ghaffarzadegan, and Larson (2018) model postdoc positions using a queuing model. Cheng (2021) finds that remaining in postdoc training for longer periods increases the chances of securing a non-tenure-track academic position at research-intensive institutions.

Table D.1: Postdoc Salary Premia by Postdoc Length

Dependent Variable: log(salary)	(3)	(4)	(5)	(6)
Panel A. All Sectors	$N = 22512$		$N = 26312$	
0 years < Postdoc Length ≤ 3 years	-0.0245	-0.0535*	0.0142	-0.00439
	(0.0293)	(0.0291)	(0.0259)	(0.0262)
3 years < Postdoc Length ≤ 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 ≤ 3 years	0.0609*	0.00406	0.0904***	0.0466
	(0.0361)	(0.0404)	(0.0323)	(0.0358)
3 years < Postdoc Length ≤ 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 ≤ 3 years	-0.0435	-0.122**	-0.0129	-0.0628
	(0.0523)	(0.0482)	(0.0459)	(0.0451)
3 years < Postdoc Length ≤ 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 ≤ 3 years	-0.0713	-0.112*	-0.0216	-0.0412
	(0.0483)	(0.0678)	(0.0440)	(0.0586)
3 years < Postdoc Length ≤ 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 for columns (3) through (6) in Table 3. The only change relative to Table 3 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 D.2: 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	...	0.0867***	0.111***	-0.0231	...
	...	(0.0258)	(0.0251)	(0.0634)	...
3 years $<$ Postdoc Length $\leq$ 6 years	...	0.199***	0.201***	-0.00460	...
	...	(0.0232)	(0.0223)	(0.0533)	...
Postdoc Length $>$ 6 years	...	0.234***	0.177***	-0.0299	...
	...	(0.0275)	(0.0298)	(0.0728)	...
R^2	...	0.256	0.270	0.460	...
N	...	4778	4778	1583	...
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 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.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

E Exploring Alternative Mechanisms for the Industry Postdoc Salary Penalty

Compensating Differential for Research Previous research 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 4 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 concentration of postdocs in research-focused positions where scientists pay to do science.[79] However, in column (4) of Table 5 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.[80]

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.[81] Column ($4''$) of Table E.1 shows that including these controls does not eliminate the industry postdoc salary penalty. While we find no evidence that employer 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.[82]

[79] However, these previous studies also provide rationale casting doubt on this mechanism as an explanation for 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.

[80] As an alternative, we consider a version of specification (4) from Table 3 which adds an indicator variable for whether an individual works in a job primarily focused on research and an indicator for if a job is primarily focused on managing people or projects: column ($4'$) of Table E.1 shows that augmenting (4) in this way has little effects on estimates, and if anything increases the magnitude of the postdoc salary penalty.

[81] 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.

[82] Davis et al. (2021*a*) 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*a*) contains a preliminary analysis of the returns to postdoc training for biomedical doctorates and finds that the postdoc salary

Seniority Pay Biomedical doctorates who forgo postdoc training to enter industry directly after graduation can build up seniority at the firm where they work earlier in their career than 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.[83] 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) and augment our specification by including a quartic polynomial in seniority. Column ($4'''$) of Table E.1 gives the results: we find that including seniority as a control in the regressions does not diminish the estimated postdoc penalty in industry.

Table E.1: Industry Postdoc Salary Premium with Alternative Mechanisms as Controls

Dependent Variable: log(salary)	(4)	($4'$)	($4''$)	($4'''$)
	$N = 6708$		$N = 6392$	
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
Postdoc Training Treated As:				
Experience	✓	✓	✓	✓
Schooling				
Controls				
Baseline	✓	✓	✓	✓
Research and Management Job indicators		✓	✓	✓
Firm Characteristics & Occupation FE			✓	✓
Seniority				✓

Notes: See notes for column (4) in Table 3. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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*a*), the results are not directly comparable—see Davis et al. (2021*a*) for a fuller discussion.

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