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ABSTRACT

We use the labor market for doctorates in the biomedical sciences, where career dislocation is common, as a case study of skill-task mismatch and its consequences. Using longitudinal, worker-level data on biomedical doctorates, we investigate mismatch as an explanation for the negative pecuniary returns to postdoc training. Our data contain unique worker-level job task information that allows us to compare the skills acquired in the years just after graduation to the tasks required in later employment. Our findings reveal a postdoc salary penalty when task mismatch is high, which is frequent, and a salary premium when skills align with tasks. Differences in accumulated task-specific human capital explain the between-sector heterogeneity in the returns to postdoctoral training, including the large and persistent salary penalties from postdoctoral training in industry, and the penalty overall. Task mismatch as a cost of pursuing risky careers in science and in other fields requiring large upfront investments in task-specific human capital has received little attention in the empirical labor literature.

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1 Introduction

In this paper, we explore the relationship between skill-specific investments and their returns for high-skill workers who face career uncertainty using biomedical PhDs as a case study. Characteristic of biomedical research career paths is the investment by young workers in skills that imperfectly transfer outside these careers along with a high likelihood of "washing out." Our focus is on the costs of misalignment between these skills and tasks in subsequent employment. We follow biomedical doctorates from the point they graduate with their degrees and must decide between entering employment and engaging in further training. About two-thirds choose postdoctoral training which involves working with an established scientist usually in a university laboratory and receiving hands-on training in basic research skills. Most doctorates see postdoctoral training as preparatory to obtaining a tenure-track position at a research university and most trainees harbor that career goal, at least at the beginning of training (Stephan, 2012; Sauermann and Roach, 2016; Nature, 2020). Doctorates on this path often string together several postdoctoral training spells, each lasting two or three years. Postdoctoral trainees typically work long hours for low pay compared to alternative employment (Stephan, 2012, 2013). It is noteworthy then that while some postdocs[1] indeed exit training into tenure-track academic positions, the majority do not, and nearly half do not enter any kind of research positions.[2] Many end up in similar positions as those from their doctoral cohort who entered the labor market directly after taking their Ph.D., but with lower earnings, this deficit persisting for years (Kahn and Ginther, 2017).

We use a task-based framework to analyze the effects of postdoctoral training on earnings and employment in the labor market. The "task approach" to labor markets treats skill as multidimensional, jobs as sets of tasks to be performed ("task requirements"), and the accumulation of human capital as task-specific. This approach has expanded economists' understanding of a range of labor market phenomena, such as employment and earnings polarization (Autor, Levy, and Murnane, 2003; Acemoglu and Autor, 2011; Autor and Dorn, 2013; Autor, Dorn, and Hanson, 2013; Acemoglu and Restrepo, 2021).[3] We use this framework to understand the trade-offs doctorates in the biomedical sciences face when pursuing a career in science. The results we produce are relevant

[1]We use the word "postdoc" as shorthand for the postdoctoral appointment and also the person holding the appointment. We employ both usages and rely on context to signal the meaning intended.

[2]The share of postdoc-trained biomedical doctorates working in industry at ten years post-PhD exceeds the share working as tenure-track researchers (28% vs. 23%).

[3]Other applications include explaining wage differences among workers of the same education and occupation (Autor and Handel, 2013; Deming and Kahn, 2018; Stinebrickner, Stinebrickner, and Sullivan, 2019), within-firm job promotions (Gibbons and Waldman, 2004), taste-based discrimination and changes in the Black-White wage gap (Hurst, Rubinstein, and Shimizu, 2021), jobless recoveries and employer "upskilling" following recent recessions (Hershbein and Kahn, 2018; Jaimovich and Siu, 2020), age-earnings profiles of workers with STEM-related degrees (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) 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 the job task 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.

for understanding the decision-making process and employment outcomes for possibly a wide range of workers pursuing careers that combine pre-investments in nontransferable skills or an extended tryout on specific tasks with low chances of entry.

Our analysis is based on longitudinal microdata on a representative sample of biomedical PhDs graduating from US universities. Like Kahn and Ginther (2017), whose analysis of biomedical postdoc training is also based on this database, we find that the earnings of biomedical doctorates with postdoctoral training are lower than those of doctorates who skipped training and that earnings differences vary substantially by employment sector. On average, postdoc-trained doctorates earn about 12% less annually compared to non-postdoc-trained doctorates. However, this earnings differential varies widely depending on occupation and sector. In industry, the salary penalty is particularly significant at 16%, which we show to be a lower bound of the true penalty under plausible assumptions about the unobserved differences between the postdoc trained and untrained. The industry penalty is of particular interest as it is the largest sectoral penalty, persisting for up to 15 years post-PhD, and the industry sector absorbs nearly 30% of postdocs and 40% of non-postdoc trained doctorates in our data. In contrast, we find a 16% salary *premium* for non-tenure-track academic research positions.[4]

Unique to our data is detailed, worker-level job task information which allows us to track the evolution of each doctorate's job tasks and directly compare the skills acquired during the early years following graduation (including during postdoctoral training) to the activities performed in future employment. We demonstrate that a *task-specific* human capital framework can explain the between-sector heterogeneity in the returns to postdoctoral training, including the sizeable penalties in some sectors. We demonstrate that the tasks performed by individuals who have completed postdoctoral training differ significantly depending on the sector in which they are employed, as does the alignment between their job tasks and the tasks they performed during their postdoctoral training. Three-fourths of all postdocs engage in basic research as their primary task during training, regardless of their subsequent employment sector (i.e., academia, industry, or government/nonprofits). However, post-postdoc employment shows considerable task heterogeneity, with basic research being the most important task only in academic jobs. We show that post-training employment salaries are higher the more aligned employment tasks are with training and that the degree of skill alignment explains most of the variation in the returns to postdoc training across sectors. Postdocs taking academic jobs experience non-negative differentials, which are positive if basic research activities are important to the job. In industry jobs, managing people or projects, applied research, development, and professional services are more commonly reported as important activities, with only 10% of postdoc-trained industry workers primarily engaged in basic research. Postdoc-trained biomedical doctorates who transition to industry face the highest degree of task mismatch compared to other sectors. The mismatch between the tasks performed as part of postdoc training and the skills required on the job in industry is enough to eclipse the positive salary

[4]These positive and negative premia are *within-sector* premia.

returns associated with the greater ability of postdoc-trained biomedical doctorates at graduation.[5] 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. The sizable postdoc salary penalty in industry highlights an important trade-off between postdoctoral training and on-the-job training for early-career doctorates in biomedical science.[6]

Most doctorates seek postdoctoral training to improve their chances of a research career. We find that postdoc-trained biomedical doctorates are 27 percentage points more likely to work in an academic research job and 21 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 percentage points more likely to obtain a research position within industry. These results appear robust to unobserved differences between postdocs and nonpostdocs at graduation. We interpret these results as also consistent with a task-based human capital model. Thus, while many postdocs leave training for non-academic and non-research jobs where they earn less than they would have had they gone straight to the labor market, postdoc training does increase the likelihood of research careers and may raise earnings conditioned on taking a research-focused job.

This paper contributes to the task-specific human capital literature. We are able to identify the actual tasks performed by individual workers on the job, and we have repeated observations of these workers, allowing us to construct a dynamic measure of each worker's task history. This contrasts with most of the job task literature which uses occupation averages of tasks performed to proxy for the tasks performed by the individual worker within that occupation (an exception is Stinebrickner, Stinebrickner, and Sullivan, 2019).[7] Having the exact job tasks of the particular job is important because job tasks can vary significantly under an occupational title (Autor and Handel, 2013; Deming and Kahn, 2018), and workers tend to match with jobs that minimize the distance between their skills and the required tasks. Assigning tasks to a worker based on occupation or job title can therefore 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,

[5]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.

[6]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 the 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."

[7]Following two cohorts of graduates of a liberal arts college, they estimate the effects of on-the-job human capital accumulation at the task level on wage levels and wage growth. The other analyses based on worker-specific task measures that we know of, Autor and Handel (2013) and Deming and Kahn (2018), are cross-sectional, relating wages and tasks in current jobs and not current wages with job task histories, as we do.

such as taking on more managerial tasks while retaining the same occupational title. Our results show the effectiveness of using longitudinal measures of worker-level tasks to capture wage variation.

In addition, we employ granular information on tasks. The task literature often lumps tasks by broad categories: cognitive vs routine and analytic vs physical, for example, task categories that are thought to divide workers in a meaningful way, such as by educational attainment or by vulnerability to automation (e.g. Autor and Handel, 2013; Acemoglu and Restrepo, 2021). This lumping also makes the analysis tractable when the workers under study are dissimilar. We look at a portion of the workforce engaged exclusively in cognitive and analytical work and even so, we show that task variation is important in explaining salary differences. This highlights the importance of identifying specific analytical tasks when analyzing wage determination within a task-specific human capital framework. Additionally, collecting data on the type and intensity of analytical tasks during academic training and the subsequent career could help in understanding wage differences among high-skilled workers. To our knowledge, this is the first study that measures education-job mismatch by relating the skills acquired during academic training to tasks performed later in employment.

Our study contributes to the literature on postdoctoral training in biomedical science and its impact on 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). Our work largely confirms the findings of Kahn and Ginther who show an overall postdoc salary penalty, wide variation in this penalty by employment sector, and a higher likelihood of employment in a research position after postdoc training. One contrast is that 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.[8] We add to their findings by showing that both the estimated benefits (i.e., increased likelihood of obtaining future research jobs) and costs (i.e., salary penalties in non-aligned subsequent employment) associated with postdoc training appear robust to plausible levels of selection bias. We show that the earnings gains for postdocs in academic jobs are likely upper-bounds while estimates of the postdoc salary penalty in industry that do not account for the positive selection of doctorates into postdocs may significantly understate this penalty. Our primary contribution to this literature is showing that the heterogeneity in returns to postdocs across sectors can be explained by the degree of task-skill alignment. The importance of task-skill alignment for explaining earnings differences and our results quantifying the differences between activities in postdocs and tasks in later employment support observations from the qualitative literature on postdocs.[9]

[8] We find a salary penalty as in Kahn and Ginther 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-tenure track research jobs were employed in such jobs at ten years post-PhD, implying significant mobility into and out of this subsector.

[9] For example, 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

The remainder of the paper is structured as follows: Section 2 gives a brief description of the labor market for biomedical doctorates that focuses on the role of postdoctoral training and presents descriptive evidence of a persistent life-cycle postdoc salary penalty for biomedical doctorates working in industry. Section 3 presents a model where salary differences between workers emanate from differences in both endowed and accrued task-specific human capital, the latter of which is a function of employment history. Section 4 describes the survey microdata used for the empirical analysis, 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.[10] Every year, a new crop of young biomedical PhDs graduate in the US and enter the job market in search of academic careers: the number of newly-graduated PhDs 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).[11] 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 expressed by the National Institutes of Health (NIH) and

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]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.

[11]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.

the National Science Foundation (NSF)—is as an academic apprenticeship for doctorates with "a temporary and defined period of mentored advanced training to enhance the professional skills and research independence needed to pursue his or her chosen career path" (Bravo and Olsen, 2007). Like an apprenticeship, postdoc positions are known for their relatively low pay, and also for their relatively long work hours: between 1995 and 2013, biomedical postdocs typically worked about 10% more hours per week for 50% of the salary compared to industry-employed biomedical doctorates of the same age (Figure A.3). Also like an apprenticeship, postdoc training is all but necessary for those who wish to fill their mentors' shoes, with 90% of both new tenure-track and newly-tenured biomedical research faculty having received training as postdocs (Figure A.4).

Nevertheless, while biomedical PhDs say they are in postdocs to obtain a tenure track research job (e.g. Sauermann and Roach), 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 other social scientists, biomedical researchers, and policy-makers.[12] 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. This is the view we investigate.

Figure 1 plots the median salary of biomedical doctorates in academia, industry, and government/nonprofits by postdoc-trained status and years since PhD graduation.[13] Postdoc-trained biomedical doctorates in industry, academia, and government/nonprofits have similar median salaries 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

[12] For example, see Freeman et al. (2001*a*,*b*), and see Stephan (2012) for a recent and comprehensive overview 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).

[13] 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.

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 non-postdocs 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 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 $\Phi_{it} = \{\phi^1_{it} \dots \phi^J_{it}\}$ where each $\phi^j_{it} > 0$ 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^j_{it} for $j \in \{1, \dots, J\}$ as follows:

$$Y_{ikt} = e^{\alpha_k + \sum_j \lambda^j_k \phi^j_{it}}, \tag{1}$$

where $\lambda^j_k \geq 0 \; \forall \; j, k$ 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:

$$w_{ikt} = \alpha_k + \sum_j \lambda^j_k \phi^j_{it}. \tag{2}$$

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):

$$\phi^j_{it} = H^j_i + H^j_{it}. \tag{3}$$

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.[14]

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.[15] 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

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

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

graduation. Then we have the following:

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

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 $\theta_{A'}^N \neq \theta_{I'}^N$.[16]

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

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

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.[17]

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

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

[17] 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.

is as a postdoc, in addition to many demographic and education variables.[18] 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.[19] For doctorates in the constructed longitudinal SDR 1993-2017 dataset, we pull any additional information regarding postdoc employment available in earlier SDR waves (1973-1991) using the 1991 SDR Longitudinal File. We then merge this dataset with the NSF's Survey of Earned Doctorates (SED), which is an annual survey given to all PhD recipients from US institutions and that contains, among other information, each PhD recipient's field of study and whether he/she intended to take a postdoc position after graduation.[20] 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.[21] 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.[22] 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

[18] 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`.

[19] 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 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.

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

[21] See Appendix B for details.

[22] 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.

observations into one of three employment sectors: academia, industry, or government and non-profits. 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.[23] 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 employment in different years.[24] 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.[25] 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.[26]

Table 2 reports summary statistics for the analytical sample broken down by postdoc-trained status and current employment sector.[27] 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.

[23] "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.

[24] 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.

[25] 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.

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

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

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.[28] Approximately three-fourths of all postdocs report basic research as their primary work activity within the first six years after graduation regardless of their subsequent sector of employment; in contrast, only 6%-15% of nonpostdocs are primarily engaged in basic research 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.[29] 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

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

[29] 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.

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 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.[30] Our preferred specification for estimating the postdoc salary premium in each sector is given by the following person-year level Mincer equation:

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

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.[31] 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,

[30]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.

[31]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.

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.[32] 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.[33] 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.[34] 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.[35] 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

[32]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.

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

[34]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.

[35]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.

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).[36] This specification is useful for measuring disparities in entry-level salaries of postdoc-trained and nonpostdoc-trained biomedical doctorates and is akin to treating postdoctoral training as a form of education (or "schooling").[37] 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

[36] 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.

[37] 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.

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.

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 on the 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 35 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.[38] 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.[39] Figure 3 plots the predicted salary profiles generated from the augmented version of specification (4) which only includes after-postdoc salary

[38]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.

[39]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.

observations and where each observation is associated with the current employment sector.[40] 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 after about 15 years post-PhD.[41] 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.[42] 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

[40]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.

[41]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.

[42]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.

tenure.[43] 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 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: "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. Few doctorates in academic tenure-track research positions took these positions straight out of graduate school (Table A.8). Moreover, most of these cases occurred early in the sample. For this reason, we do not consider the estimates in Panel A reliable but include them for completeness. 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.[44]

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.[45] The salary advantage of postdoc-trained biomedical doctorates

[43] 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.

[44] 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).

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

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 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. Our estimates of the benefits of postdoc training are likely upper-bounds, however, while the estimated magnitude of the postdoc salary penalty in industry is likely a lower-bound of the penalty.[46] 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.

Panel B column (4) of Table 5 shows that postdoc-trained biomedical doctorates working as non-TT academic researchers earn more than their nonpostdoc-trained counterparts. While this suggests 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.[47] This result is consistent with postdoc training being an effective way

[46] 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).

[47] 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. Note that the finding of zero earnings effect for academic non-research positions is an upper bound, meaning that the earnings effect in academic non-research positions could be negative.

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.[48] 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 within field-by-cohort sector-specific postdoc salary effects.[49] 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. 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).[50]

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.[51] 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.

[48]See Footnote 19 for the list of 14 work activities/tasks included in the SDR.

[49]These are the estimates found in column (4) of Panel C in Table 3, resulting from regressions that treat postdoc training as experience and limit the sample to exclude observations for years when biomedical doctorates are employed as postdocs.

[50]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.

[51]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.

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 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.[52] 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).[53] Results are consistent across specifications, with point estimates declining by between 43% and 66%. 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.[54]

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

[53]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.

[54]See Table A.9 for regressions on the full sample and academic and government/nonprofit sectors where task

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., 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.[55] The constructed measure of task distance thus ranges from zero to one, with a value of zero for doctorates whose percentage of time spent on each task during their first six

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.

[55] 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

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

years post-PhD exactly matches the percentage of time spent on each task in current employment and a value of one if there are no tasks in common between the two periods.[56]

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 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.[57]

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

[56]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.

[57]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.

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.[58] 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.

7 Discussion of Results

We find that in the period between six and twenty years after the PhD, postdoc-trained doctorates earn 11.7% less annually compared to non-postdoc-trained doctorates, controlling for individual-level characteristics, a quartic polynomial in experience, PhD university (i.e., *alma mater*) fixed effects, and field-by-cohort fixed effects. These differences vary by sector 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. Our evidence suggests that the estimated 15.8% postdoc salary penalty in industry is a lower-bound for the true penalty of postdoc training on industry salary implying that biomedical doctorates who first pursue postdoc training prior to employment in industry are on average of greater ability at PhD graduation compared to their nonpostdoc-trained counterparts. 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% in such jobs, implying that selection bias attenuates rather than exaggerates the impact of postdoc training on salary in academic non-tenure-track research positions. While postdoc-trained doctorates in industry are more likely to be conducting research in their jobs, we find no evidence that the sizeable industry earnings penalty is a compensating difference for the ability to conduct research or for other tasks as part of current employment.[59]

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 employ-

[58] 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.

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

ment. One focus of the paper is industry employment, which absorbs nearly 30% of postdocs, and where the postdoc earnings penalty is largest. First, we document substantial differences in the tasks emphasized in postdoc training and in subsequent 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%) and renders 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. We find that task histories account for most of the salary differences between postdoc-trained and nonpostdoc-trained doctorates in the other sectors. We also find that the postdoc salary premium is higher (or the deficit lower) for jobs that are more like postdocs. Once we control for the task distance between postdoc and post-postdoc employment we account for most of the postdoc's effect on earnings. Postdoc-trained biomedical doctorates are more likely to secure research-focused positions, both in academia and industry, compared to their nonpostdoc-trained counterparts, with estimates robust to selection on unobserved ability at time of PhD graduation. Postdoc training increases one's chances of obtaining an academic tenure-track research position by about 20% and an industry research position by 12%. Taken together, our results are consistent with postdoc training augmenting skills relevant to research, especially basic research, rather than only serving as a holding tank or as a signal of pre-existing ability. [60]

A task-specific human capital explanation is consistent with the views of those within the biomedical science 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.[61] 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.[62] Our results

[60]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 discussions of postdoctoral training as queuing in which the postdoc might act as a holding room for biomedical PhDs awaiting tenure-track offers see Hur, Ghaffarzadegan, and Hawley (2015) and Andalib, Ghaffarzadegan, and Larson (2018), and as tournaments in which young doctorates compete through research effort in the labs of established researchers to win tenure-track positions see Freeman et al., 2001*a* and Freeman et al., 2001*b*.

[61]As just one example, 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 on BEST, see `https://commonfund.nih.gov/workforce`, Meyers et al. (2016), and Lenzi et al. (2020).

[62]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.

suggest that making room for training in skills valued in industry would lessen the postdoc salary penalty in industry. They do not indicate whether such changes would make postdoctoral training more attractive to doctorates, improve trainee satisfaction with postdoctoral training, or, more generally, improve social welfare; these questions are beyond the scope of the paper.

Similar to the findings in past research on biomedical postdocs, our findings show that biomedical doctorates pay an earnings price for postdoctoral training and for choosing academic careers. Our back-of-the-envelope calculations suggest that, on average, those headed to a career in industry after their postdoc will be paid $366,000 (discounted annually at 3%) less in their first 20 years post-PhD than their nonpostdoc-trained counterparts who entered industry after graduation.[63] However, a postdoc who lands a job in industry will still be paid $339,000 (discounted) more than the average postdoc who subsequently works in academia.[64] Combining results, the average postdoc-trained biomedical doctorate who works in academia earns $740,000 (discounted) less than the average nonpostdoc-trained biomedical doctorate working in industry in their first 20 years post-PhD, for an average of $37,000 less per year.

8 Conclusion

This paper contributes to the growing empirical literature in labor economics that views tasks as fundamental to human capital acquisition and wage determination. First, we identify an environment where workers commonly experience large, abrupt dislocations between job tasks and task-specific skills. The market for researchers in biomedical science is 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. Their experience contrasts with the general tendency of employment changes occurring to minimize task distance (Gathmann and Schönberg, 2010; Guvenen et al., 2020). The returns to a postdoc training and earnings varies by sector, as shown in previous research. As postdocs are largely homogeneous in the skills transferred (they focus on basic research skills), our estimates are showing that task mismatch is important to explaining between-sector heterogeneity in the returns to training of a given type in a case where such returns range from significantly positive to significantly negative.

Our second contribution is showing 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

[63] 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.

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

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. Our work can also be framed in terms of education and job match. Recent studies have examined the earnings consequences of mismatches among workers of the same level of educational attainment (Nordin, Persson, and Roof, 2010; Robst, 2007, e.g.,). To our knowledge, ours is the first work that relates the skills workers acquire during academic training—as measured by the activities that comprise that training—to the precise tasks that require those skills in later employment.

Third, this work further demonstrates 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 (e.g. 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 studied two cohorts of students graduating from a Kentucky liberal arts college. Our study of a nationally-representative sample of biomedical doctorates graduating over the course of two decades helps to demonstrate the broader relevance of task tenure to wage determination.

Finally, our study documents an under-explored type of skill mismatch in the empirical labor literature. Our interpretation of the postdoc decision is that the additional, highly specialized training is a gamble that sometimes pays off with an academic research career and job tasks well-matched to her skills, but often does not. Past research has shown that PhDs pay for the opportunity to conduct research with lower starting wages (e.g., Stern, 2004). We find that PhDs who take the postdoc route and "win" (that is obtain an academic position) earn \$740,000 less than the PhD who goes directly into industry in the twenty years following the PhD. But we also show that ex ante skill mismatch is another compensating difference for a chance at participating in science. Specifically, we show that if postdocs had gone directly into industry they would have earned, on average, at least \$366,000 in discounted terms more within the first 20 years after receiving their PhD, and that this difference is mostly caused by the gap between the skills learned during the postdoc and the tasks required in industry jobs.

We study a career that requires a significant pre-career investment in non- or weakly-transferable human capital to obtain a chance of access. Skill mismatch arises in these careers because the young worker must make her investment decision before knowing her abilities or preferences. We believe the phenomenon we document among biomedical doctorates is important in other corners of the workforce. Skill mismatch leading to salary penalties is likely a structural feature of career paths in which the worker faces uncertainty—in ability, talent, the quality of one's ideas, and/or one's preferences—that can be resolved only after extensive training, apprenticeships, or other specific investments.[65] This uncertainty would seem more likely where job tasks are non-routine and highly differentiated, such as the creative fields, which include the sciences and the arts.[66] Further investigation into the importance and implications of a large skill mismatch generated by an up or out process in specialized labor markets would expand our understanding of occupational choice and wage dynamics within and across careers and workers.

[65] The theoretical literature on skill uncertainty and job mobility dates back to at least the 1970s (Johnson, 1978). MacDonald (1988) models a setting that is relevant to our case, where the market is uncertain about worker ability and where ability is revealed only by trying the job. The motivating example is a performer in the entertainment industry. An implication of his model is that in equilibrium, more young workers try the job than eventually make a career in it, and when trying out, young workers receive much lower wages compared to alternative employment (are "starving artists"), but are highly rewarded if they succeed. MacDonald points to an extension of his model whereby young performers invest in training to obtain useful information on their talent before attempting the career (p. 166). In Guvenen et al., 2020, precisely this mechanism explains why workers might invest in skills that are at risk of not being used.

[66] See Menger's recent survey of the economics and sociological literatures on artistic careers (Menger, 2006). The uncertainty faced by artists early in their careers is a common focus of this research and the career dynamics documented for artists resemble those of biomedical doctorates seeking careers in bench science. An aspiring opera singer, for example, may spend years in voice training before discovering she lacks the talent to make a career as a performer, and then end up, like many young persons who train in the arts, in unrelated employment (Alper and Wassall, 2006).

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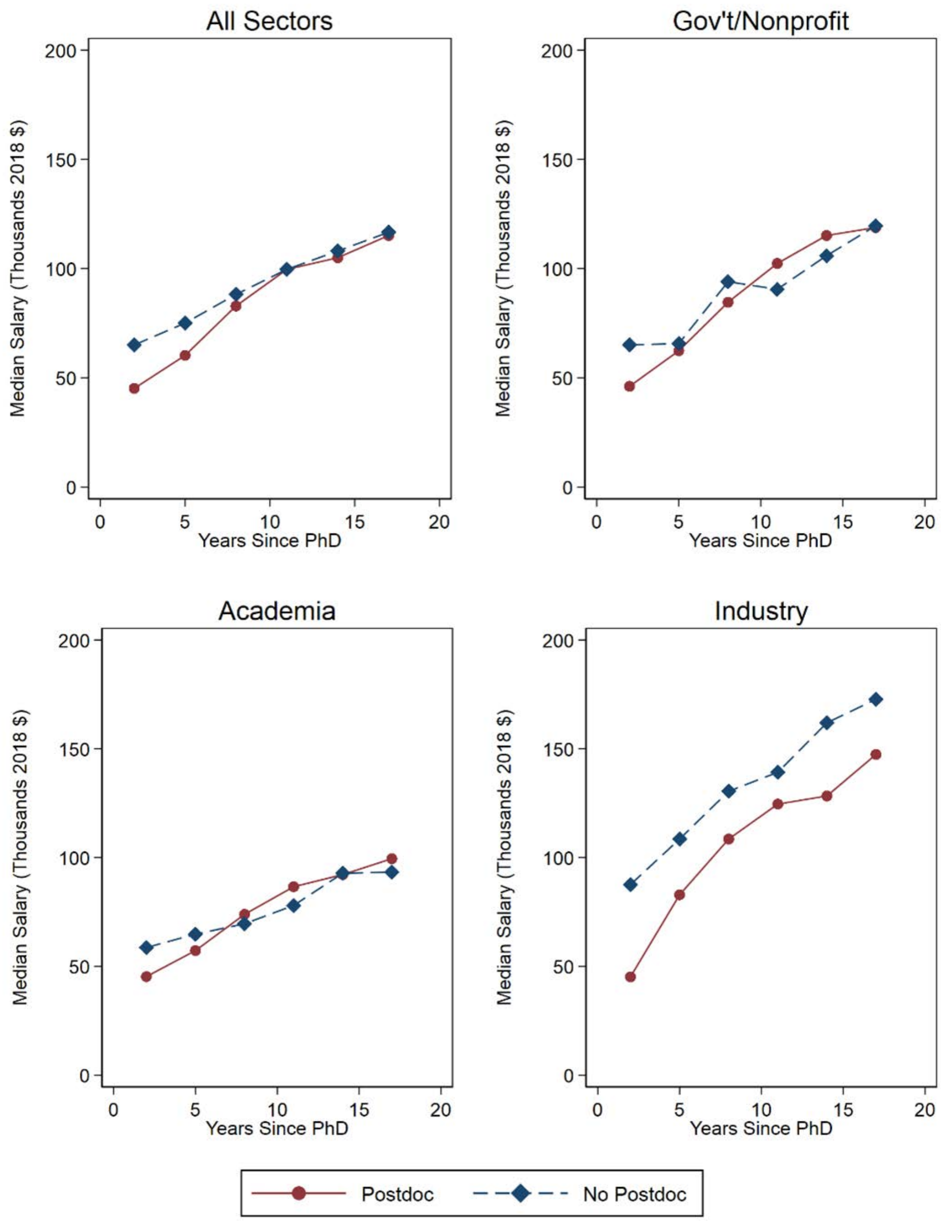
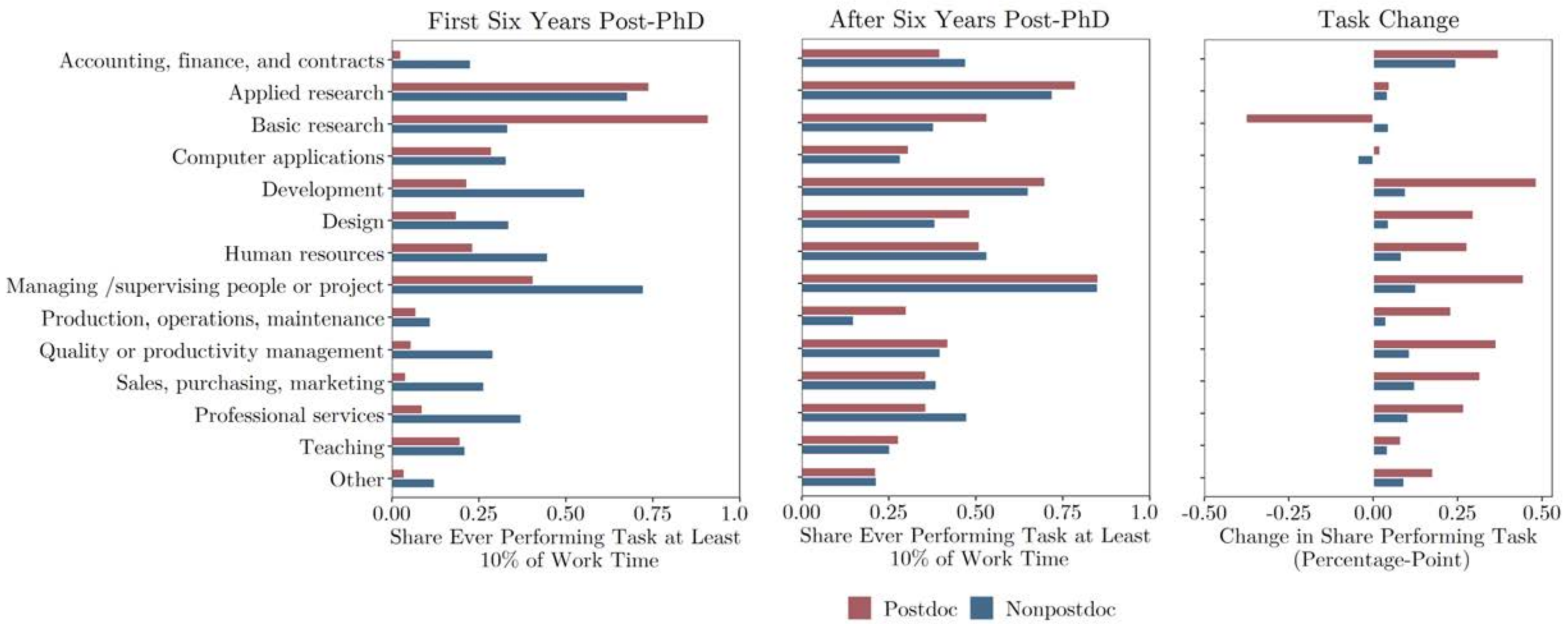
Figures and Tables

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



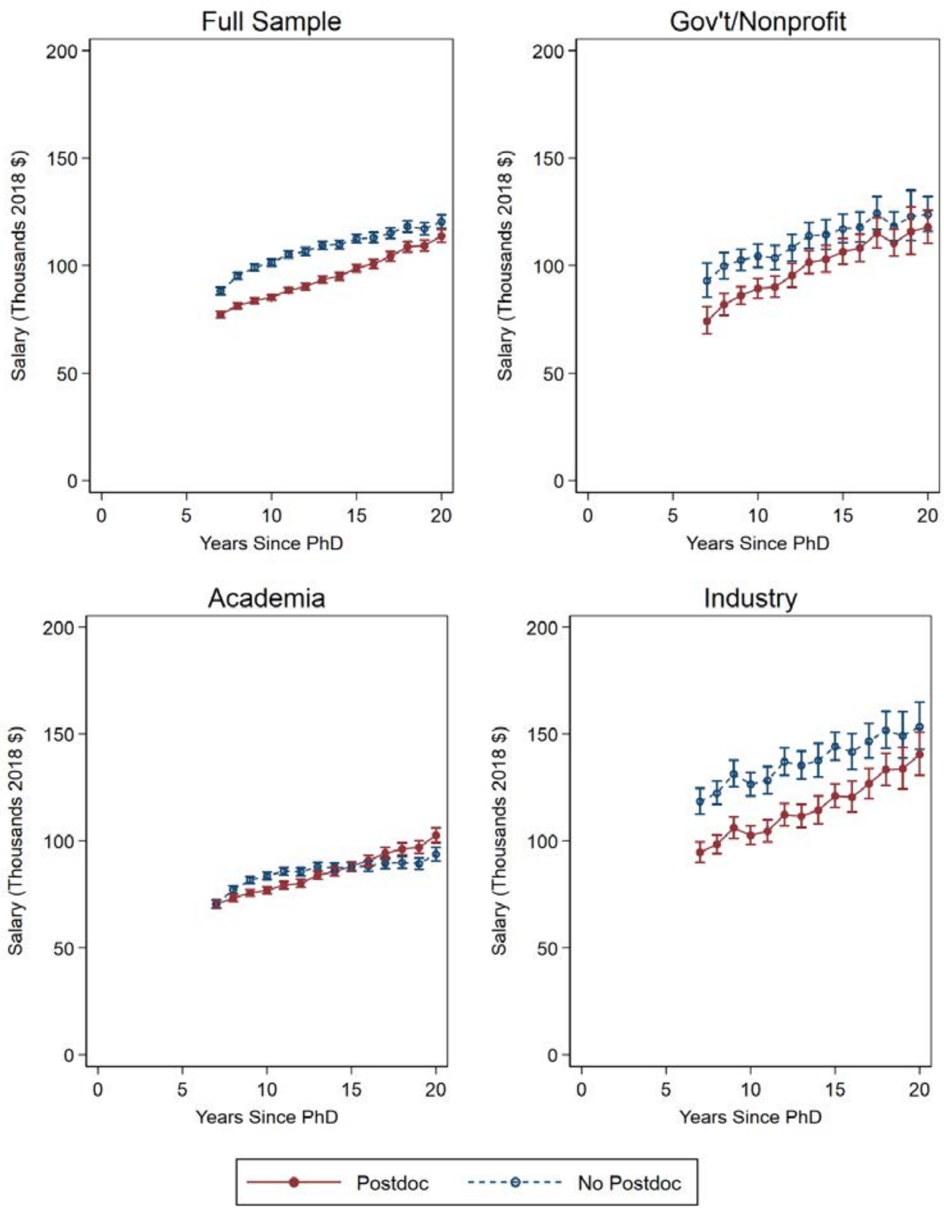
Notes: Figure 1 shows the median salary in each 3-year interval since PhD for biomedical doctorates first appearing in the SDR 1993, 1995, or 1997 waves and who graduated no earlier than 1990. Biomedical doctorates are associated with the employment sector (academia or industry) that they occupy at 10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

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



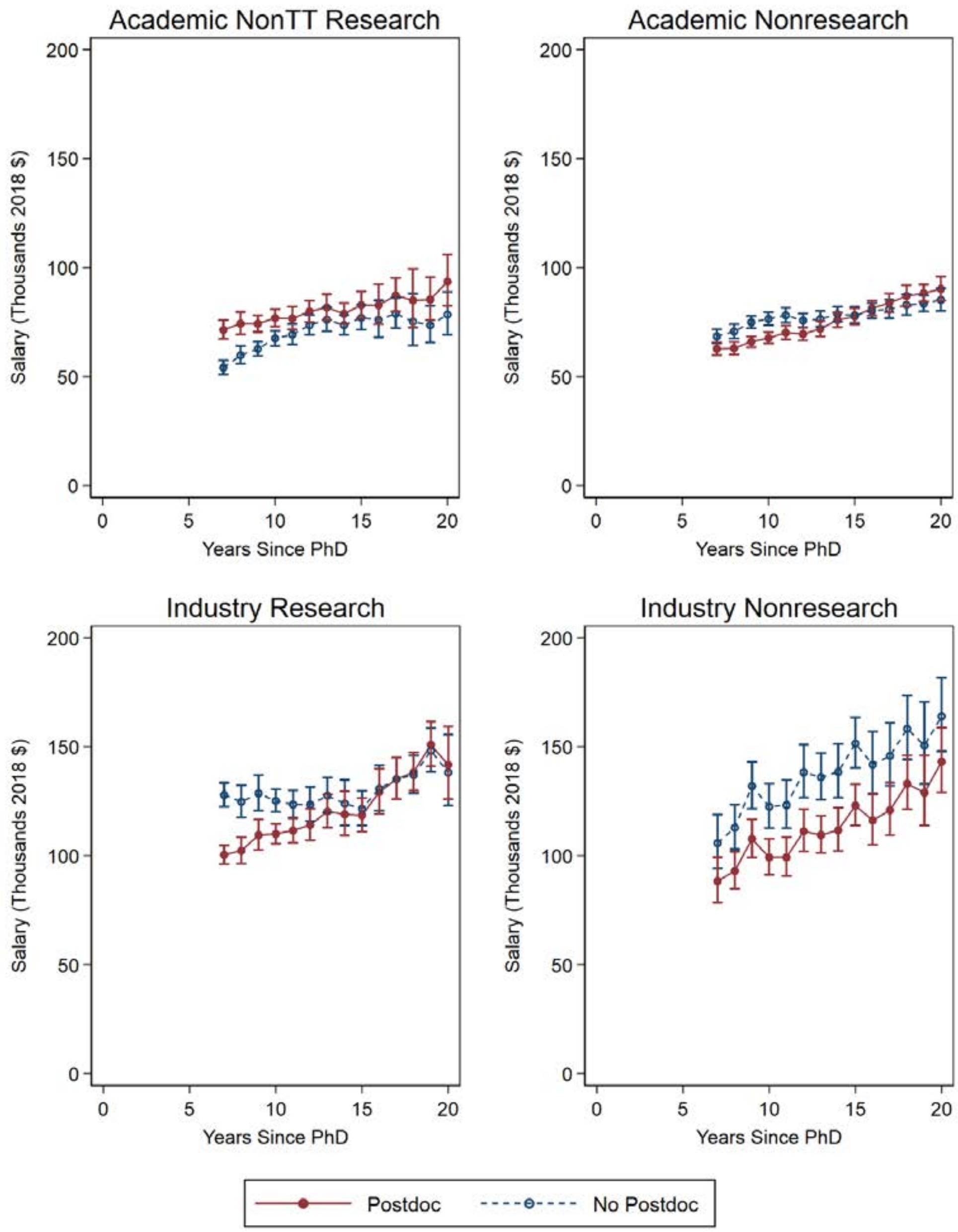
Notes: Figure 2 gives the change in the share of postdocs and nonpostdoc performing tasks for at least 10% of work time among biomedical doctorates working in industry. The tasks performed by postdocs in their first six years represent the tasks performed as part of postdoc training. Greater magnitudes 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$