

Exposure to Science and Scientific Careers: Evidence from Minimum Wage Increases and University Lab Employment*

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Abstract

We study how exposure to scientific research in university laboratories influences students' pursuit of careers in science. Using administrative data from thousands of research labs linked to student career outcomes and a difference-in-differences design, we show that state minimum wage increases reduce employment of undergraduate research assistants in labs by 7.4%. Undergraduates exposed to these minimum wage increases graduate with 18.1% fewer quarters of lab experience. Using minimum wage changes as an instrumental variable, we estimate that one fewer quarter working in a lab, particularly early in college, reduces the probability of working in the life sciences industry by 2 percentage points and of pursuing doctoral education by 7 percentage points.

JEL codes: I23, J30, O30.

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1 Introduction

Careers in science often begin with apprentice training. Postdocs, graduate students, and undergraduates work in laboratories alongside more experienced researchers, receiving both hands-on training and exposure to the profession. These workers are typically paid low wages, in part, because their compensation reflects not only the marginal product of their labor but also the value of the training they receive. When policies mandate that trainees' wages be increased, such as through increases in the minimum wage, some trainees may lose opportunities for exposure to scientific work, and ultimately, alter the rate they pursue scientific careers ([Hashimoto, 1982](#)). A well-trained scientific workforce is important for innovation and long-run economic growth, making it critical to understand how policies affect the pipeline of trained scientists ([Romer, 1990](#); [Kahn and Ginther, 2017b](#)).

In this paper, we demonstrate that university labs reduce the employment of undergraduate research assistants following minimum wage increases. These reductions have significant impacts on the likelihood that undergraduates pursue scientific careers. Using a panel dataset of labs and their employees across 32 U.S. universities between 2001 and 2019 and a staggered difference-in-differences approach, we show that following minimum wage increases, labs decrease the employment of undergraduates by 7.4% on average.¹ Building on this, we then use minimum wage changes as an instrument for students' exposure to laboratory research during college. Using data on 20,000 individual undergraduates' employment during college and eventual career paths, we find that reduced exposure to lab work, particularly early in college, significantly decreases the probability of pursuing a scientific career.

Our analysis combines multiple datasets to examine these dynamics. We analyze how labs respond to increases in state minimum wages using detailed administrative data from the accounting records of thousands of labs at U.S. research universities contained in the UMETRICS database. For tracking students' career outcomes, we leverage a match between the employment records of student trainees in labs in the UMETRICS data with information in Steppingblocks, a database of information about university alumni's educational achievements and employment histories. Combined with information on state minimum wage changes, we are able to analyze effects on employment in labs, the

¹We calculate an own-wage elasticity of -0.469, using a sub-sample of our data for which we can impute both labor costs associated with undergraduate workers and the hours worked by those undergraduates (see details in Appendix D). This estimate falls in the "medium negative" range relative to other minimum wage studies as presented in [Dube and Zipperer \(2024\)](#).

time individual students worked in labs during college, and their subsequent career outcomes.

In our empirical work, we start by estimating the effects on employment in labs and the exposure of lab trainees to scientific work. In the short-run, PIs face budget constraints that are fixed at the time of grant award, so higher wages may require cutting back on labor or reallocating work among personnel. We find that scientists employ 7.4% fewer undergraduate research assistants in response to minimum wage changes. We find especially pronounced declines in labs that employed more undergraduates prior to the minimum wage change. We also document that labs slightly increase their use of graduate student labor, suggesting that some tasks previously done by undergraduates may be shifted to graduate students.

We also examine if labs are able to offset increased labor costs by securing additional funding or by shifting scientific work to collaborators in states with potentially lower labor costs. For example, PIs can apply for more funding to compensate for the increased labor costs. Indeed, we find that PIs are 8.46% more likely to utilize supplemental funding, additional funds provided by funding agencies to previous grantees, in response to the higher labor costs. Funding agencies do not appear to increase funding commensurate with rising labor costs, however, and a back-of-the-envelope calculation suggests that it would cost funding agencies over \$133 million dollars in additional funding per year to fully restore employment in university labs.

Our findings are in line with recent work showing larger negative employment effects of minimum wages in tradable sectors, where there are fewer opportunities for cost pass-through and firms face tighter constraints on adjusting margins ([Harasztosi and Lindner, 2019](#); [Gopalan et al., 2021](#)). University labs, which tend to produce non-market outputs like scientific publications and operate under rigid budget constraints, resemble such settings. In this context, our results interestingly illustrate the *opposite* of the Le Chatelier principle: the inability to pass through costs may actually amplify short-run employment responses when compared to settings with more flexible adjustment channels.

Importantly, the increased labor costs impact the exposure of student trainees to scientific work. We show that undergraduates at universities that experienced minimum wage increases worked 18.1% fewer quarters in labs during their college years, particularly during their first and second years. However, this effect was less pronounced for students supported by the Federal Work-Study program, which subsidizes wages for students with financial need.

Having documented the effect of minimum wage increases on exposure to scientific work, we examine whether the decreased time working in labs influences students' subsequent career paths.

Leveraging minimum wage increases as an instrumental variable for the time employed in labs, we show that the decreased exposure to scientific work translates into significantly lower rates of undergraduate research assistants pursuing doctoral degrees or working in the life sciences sector after graduation. We find that working one fewer quarter in a lab during an undergrad student’s college years translates into between a 7.0 and 10.3 percentage point decrease in the rate of enrolling in a doctoral-level program. Given our sample of 28,283 students, this implies that if all students had experienced a minimum wage increase, roughly 500 fewer undergraduates in our sample would have pursued these advanced degrees.

The life sciences sector is often a desirable career path for students trained in research-intensive environments, especially in areas aligned with federally funded biomedical research through the National Institutes of Health (NIH). We find that reduced lab experience for students working in NIH-funded labs reduces the likelihood that students are later employed in the life sciences industry.

Our findings contribute to three strands of literature. First, we add to research on entry into STEM careers and the pipeline of scientists. Exposure to research experiences can shape students’ career choices by providing information about career paths, building skills, and connecting them to mentors ([Arcidiacono, Aucejo and Hotz, 2016](#)). A well-trained scientific workforce is central to long-run growth ([Romer, 1990](#)), and prior work shows that differences in exposure to innovative environments can play a role in determining who pursues scientific careers ([Kahn and Ginther, 2017a](#)). For example, research on the “lost Einsteins” phenomenon demonstrates that lack of exposure to science and innovation activities reduces the likelihood that talented individuals pursue these careers ([Bell et al., 2019](#)). Our results show that labor market policies such as minimum wages can also shape this pipeline by constraining undergraduates’ access to lab experiences that influence their long-run career trajectories.

Second, we contribute to the economics of science and innovation literature on knowledge production and the scientific workforce. Prior research has estimated the long-term effects of shocks to inputs in science, such as physical and human capital destruction ([Waldinger, 2016](#); [Baruffaldi and Gaessler, 2018](#)), impacts of computing resource constraints ([Boudou and McKeon, 2024](#)), and the death of important collaborators ([Azoulay, Graff Zivin and Wang, 2010](#)). In addition, research has examined the effect of delays in access to funding ([Tham, 2023](#); [Tham et al., 2024](#)) and increases in funding for research labs ([Myers, 2020](#); [Rosenbloom et al., 2015](#)). Unlike the physical destruction of tangible assets, constraints to accessing computing resources, or the death of collaborators, where an input becomes unavailable or scarce, our study examines how scientists react and adjust to changes in the relative

prices of available inputs. Unlike shocks that increase or decrease total available funding for a lab, our analysis examines situations in which a specific input price changes and traces the adaptation of scientists in response.

Two studies speak more directly to the role of input prices in scientific production. [Goolsbee \(1998\)](#) finds limited labor supply responses to wage changes among R&D workers, while [Furman and Teodoridis \(2020\)](#) show that declining prices of a computational input affect the research direction of established scientists. In contrast to both, we examine how rising labor costs affect the demand for student workers and how these changes influence the careers of early-stage trainees. While earlier work has emphasized the important role of students and postdocs in research production ([Carayol and Matt, 2004](#); [Stephan, 1996](#)), research also points to the important role of training for scientific career paths ([Kahn and Ginther, 2017b](#)). Our study fills a gap in empirical evidence on how scientists allocate student labor in response to wage changes ([Carayol and Matt, 2004](#); [Stephan, 1996](#)). In addition, our work demonstrates that labor cost changes impact student trainees' career path decisions, an aspect that has yet to be examined carefully in the literature.

Finally, we provide new evidence for the labor economics literature on the impacts of the minimum wage. While a large literature examines how firms respond to changes in the cost of labor inputs, such as minimum wage increases², much less is known about how labor cost increases affect institutions outside of traditional firm settings. In particular, very little is known about employment in university research labs, where principal investigators (PIs) produce scientific knowledge while also training future scientists. Furthermore, the findings in the current literature about firms are unlikely to apply to university labs and the career paths of student trainees. Firms often absorb minimum wage increases through productivity gains and price pass-through ([Dube and Lindner, 2024](#); [Rao and Risch, 2024](#)). However, unlike most firms, university labs cannot pass higher labor costs onto consumers, as their primary outputs, scientific publications and trainees, are not priced. They also typically operate under fixed grant budgets, which limits their ability to adjust expenditures in the short run. Thus, labs may be particularly sensitive to increases in labor costs and more likely to reduce employment of trainees. Because scientific training is often done through an apprenticeship model, reductions in undergraduate research opportunities may have significant downstream effects on students' career

²Recent papers include [Cengiz et al. \(2019\)](#); [Dustmann et al. \(2021\)](#); [Clemens \(2021\)](#); [Manning \(2021\)](#); [Derenoncourt and Montialoux \(2020\)](#); [Coviello, Deserranno and Persico \(2022\)](#); [Jardim et al. \(2022\)](#); [Azar et al. \(2023\)](#); [Berger, Herkenhoff and Mongey \(2025\)](#); [Rao and Risch \(2024\)](#).

trajectories.

Most research in this area focuses on low-wage workers who would be most likely to be impacted by the increases, typically working in sectors like fast-food or retail. A growing set of papers has examined the impact of minimum wages in new settings, such as the non-profit sector ([Meer and Tajali, 2023](#)) and childcare ([Brown and Herbst, 2023](#)). Due to data limitations, however, few papers have explored the impact of minimum wage changes on undergraduate student labor. Furthermore, to our knowledge, no previous study has examined how the minimum wage impacts student and trainee employment in university labs, providing important experience and exposure to students considering scientific careers.

Finally, recent research on the impacts of the minimum wage has tended to find little evidence of disemployment effects ([Cengiz et al., 2019](#)) and reallocation of workers to higher-wage and higher-productivity establishments ([Dustmann et al., 2021](#)). The reason for the small or null effects may be in part because firms are able to pass on cost increases to consumers. In our setting, however, labs produce unpriced goods, such as scientific papers, and thus have limited means to defray the impact of cost increases in the short-run. In contrast to the literature on employment in the business sector, we discover significant negative employment effects on undergraduates students.

Our findings also have important implications for policymakers. Given the uncertainty of price changes for these specialized inputs, our results point to the need for insurance mechanisms or increased budget flexibility by funders and university administrators. Universities seeking to provide undergraduates with research experience should consider providing faculty with alternate funding sources that are in line with minimum wage levels.

In the next section, we discuss the data we use and provide background about minimum wage changes we use in our analysis. In Section 3, we describe the empirical strategy. In Section 4, we present the results, followed by the conclusion.

2 Data

Our analysis uses data linked from multiple data sources that provide information on university lab expenditures, employment, and scientific research outputs.

Our primary data source is the UMETRICS database, a collection of administrative records from contributing universities in the United States ([Lane et al., 2015](#); [The Institute for Research on Innovation & Science, 2022a,b](#)). The records in this database represent charges to sponsored research grants.

These transactions include payments to vendors as well as the employment of workers. Transactions that represent the employment of a worker include the occupational title of the worker and the number of days that the worker was paid from the associated grant. The UMETRICS data covers the time period between 2000 and 2022.³

For our analysis, we focus on transactions associated with research grants between 2000 and 2019.⁴ Only grants that pay a faculty member are included. We exclude grants that fund whole centers or departments by removing grants that pay more than 12 distinct faculty members⁵ or that are NIH grants specifically meant for funding a research center.⁶ Finally, the grants in our sample must both employ workers and make purchases from a vendor at some point during our sample time period.⁷

2.1 Analytical Datasets

Using the raw UMETRICS data, we derive four datasets for our analysis.

2.1.1 Lab Panel Dataset

We create a panel dataset that tracks employment in labs over time. As UMETRICS does not have identifiers for labs, we construct labs by identifying individuals who are PIs and all the grants associated with that individual. Specifically, for each person considered a PI, based on being employed exclusively as a faculty member for at least three years, we find all the grants that paid that individual over time. We define a PI and the grants that paid them as a lab for the purposes of our analysis.

We transform the UMETRICS data into a lab-by-quarter dataset by aggregating all spending and employment across the grants of a lab in each quarter. Each lab-by-quarter observation includes the following variables: the total spending at vendors, the number of days of employment for postdocs, graduate students, undergraduates, and research staff, and the number of distinct employees for each

³Each contributing university in the UMETRICS sample joined and began contributing data at a different time. Documentation on the number of universities contributing data in each year can be found in the UMETRICS documentation at <https://iris.isr.umich.edu/research-data/2020datarelease/>.

⁴We cut the data at 2019 in order to avoid the disruption that occurred during the COVID-19 pandemic.

⁵We use this cutoff as it represents the 99th percentile in the number of distinct faculty members paid a grant in our data.

⁶We exclude NIH grants with activity codes such as G12, M01, P01, P20, P2C, P30, P40, P42, P50, P51, P60, PL1, PM1, PN1, PN2, T42, U48, U54, UL1, and ULTR.

⁷We make this restriction in order to focus on active research labs. Note that vendor payments are broadly defined. For example, airline tickets for attending a conference could appear in vendor spending. In Appendix L, we repeat our main analysis but remove this restriction. The results are similar.

of the preceding occupations.⁸ For a limited set of PIs, we also know information about which department they are associated with.

While UMETRICS does not provide the wages of individual workers, we impute the total labor costs of labs by subtracting vendor and subaward costs from the direct costs of the labs (Harasztosi and Lindner, 2019).⁹

Some labs may not have active grants or transactions in every quarter. Therefore, we balance the observations of labs between the quarter in which we observe their first transaction and their last observed transaction. More details about the dataset construction are provided in Appendix A.¹⁰

As our main regressions include fixed effects at the lab level, we also drop any labs without variation in the number of days of undergraduate work. These “singleton” observations have been shown to be problematic for inference and are dropped by default in many statistical packages (Correia, 2015). Therefore, in order to be consistent across regressions, we impose this restriction.

Ultimately, this panel dataset contains 264,951 lab-by-quarter observations. As shown in Panel B of Table 1, the average lab spends \$112,828.28, employs 1.19 undergraduate research assistants and employs 1.88 graduate students, per quarter.

2.1.2 Scientific Production Dataset

While our analysis of employment in labs over time is at the quarter level, in order to examine the effects on the production of scientific papers, we also create a lab-by-year panel dataset.¹¹ For each observation in the lab-by-year panel, in addition to aggregating the total spending and employment across each lab’s grants over the year from UMETRICS, we also link the number of scientific papers published in that year that cite one of the grants funding the lab. For each grant associated with

⁸We use the number of days of labor, which is in contrast to others who have used the total wage bills as outcomes in order to adjust for differences in quality of workers (Fox and Smeets, 2011; Akerman, Gaarder and Mogstad, 2015). In this setting, postdocs, graduate students, and undergraduate workers are likely paid one wage within occupational band.

⁹This imputed measure of labor cost is noisy since some universities do not provide UMETRICS with information on all internal payments to departments within the university. Thus, the labor costs we estimate are likely an upper-bound on the true labor costs of a lab.

¹⁰Our method for imputing labs and aggregating transactions is similar to other papers using UMETRICS data, such as Ross et al. (2022).

¹¹We can not assign published papers to the precise quarter in which the research for that paper was conducted. Moreover, while some publications have information about the particular month or quarter in which they were published, it is hard for us to associate a publication with the exact quarters in which the work was conducted for that publication.

each lab, we searched and collected all of the publications in the *Web of Science* bibliometric database that acknowledge that grant or list the PI as an author. In addition, we collected all the publications listed in the *PubMed* database that are linked to the grants of a lab or the lab’s PI based on a linkage constructed by IRIS. As a measure of the impact of these publications, we collect the total number of forward citations to the *Web of Science* publications during the subsequent five years as well as whether or not the *Web of Science* publications would be classified as “disruptive” using data from Funk and Owen-Smith (2017).

After dropping singleton observations, this panel dataset contains 72,684 lab-by-year observations. As shown in Panel D of Table 1, on average a lab has 0.47 publications per year listed in *Web of Science* and 3.07 listed in *PubMed*. The higher number of publications in *PubMed* is reflective of the fact that the crosswalk between the UMETRICS data and the *PubMed* database was produced using a more robust method.¹² While the crosswalk to *Web of Science* is less comprehensive than the one to *PubMed*, we use both in our analysis since only *Web of Science* has data on forward citations and the measure of the disruptiveness of the publications.

2.1.3 Undergraduate Individual Panel Dataset

We also construct an individual-by-quarter panel dataset for all undergraduates to examine how minimum wage changes affect undergraduate employment across research labs. For each undergraduate observed working in a lab in the UMETRICS data, we create a balanced panel with eight quarterly observations, beginning from their first recorded lab employment. In each quarter, we flag whether the student is employed in any research lab, allowing us to track whether students who leave one lab find work in another.

We also identify whether a student receives funding through Federal Work Study (FWS) by flagging those paid from accounts with “Federal Work Study” or variations in the title. Additionally, we record students’ gender, as inferred by UMETRICS through imputation based on first names. To assess whether undergraduate research assistants work in more or less productive labs over time, we also link each student’s employment with the annual publications produced by the lab they are employed in. We compute a z-score comparing that lab’s output to other labs at the same university in

¹²IRIS, the maintainers of the UMETRICS database, created the UMETRICS-PubMed crosswalk. They were able to utilize PI names and additional data to match articles to UMETRICS. In contrast, the UMETRICS-Web of Science crosswalk was created using only non-PII information, such as grant numbers.

the same year, and in the same field.¹³ This enables us to say if students who remain employed in labs are more likely to work in higher or lower productivity labs. We also measure the relative size of each lab by computing a z-score based on the number of undergrads employed in a lab in a year quarter relative to other labs at the same institution.

This panel dataset contains 192,529 undergraduate-by-quarter observations for 26,497 undergraduate students. On average, as shown in Panel F of Table 1, 29% of the observations in this dataset are female undergrad RAs and 12% are FWS students. Across the dataset, 42% of the observations are associated with a student paid by a lab at their university.

2.1.4 Student Outcomes Dataset

Many of the employees in the UMETRICS database are linked by IRIS to data from Steppingblocks, a dataset that contains information on individual-level educational achievements and careers. We use this information to create a dataset with the employment of undergraduate research assistants during college along with their educational and career outcomes. Specifically, for each UMETRICS employee with a listed bachelor's degree year, we compute the amount of time that employee worked during their undergraduate years (e.g. from September, four years before their graduation year until June of their graduation year). We measure the time as the number of quarters in which the student worked in one of the labs in the sample used for our lab panel dataset described above. As outcomes, we flag if the Steppingblocks data list the individual as going on to a doctoral-level degree program, and if the individual lists employment in the life sciences industry.¹⁴ We focus on students whose undergraduate years began and ended during the time when the UMETRICS database had employment data coverage for the university they attended as undergrads. We also only include individuals who worked at least some time recorded in UMETRICS during their undergraduate years.¹⁵ Finally, we restrict to those individuals who began college after the start of UMETRICS coverage for that university and ended college before the end of coverage. We make this restriction in order to ensure that we observe all potential employment of a student in a lab during their college years.

¹³We only know the exact field for a limited set of labs. For the remaining labs, we pool the labs together and compute the z-score based on this collection of labs in an "unknown" department.

¹⁴Steppingblocks includes among doctoral-level degrees doctorates of philosophy as well as doctorate of medicine and juris doctorate degrees.

¹⁵We make this restriction as we are only able to pull data from Steppingblocks based on the employee IDs that appear in the UMETRICS employment data.

This dataset, which we refer to as the Student Outcomes Dataset, contains 28,283 student observations, including their employment during college and career outcomes. Among the students in our linked dataset, all of whom worked in a research laboratory at some point, 17% go on to pursue a doctoral-level degree. On average, those students worked 1.44 quarters in research labs while they were undergraduates. Of the labs they worked in, on average, these students spent 0.69 quarters working in NIH sponsored labs.¹⁶

2.2 Minimum Wage Data

For each observation in the above-described datasets, we attach the effective state minimum wage at that time as well as if the minimum wage changed. For each university in our dataset, we identified the effective minimum wage based on the geographic location of the university. The minimum wage data comes from [Zipperer and Vaghul \(2016\)](#). The effective minimum wage is defined as the maximum of the federal minimum wage and the minimum wage of the state in which the university is located. Some universities have a different effective minimum wage than the state minimum wage because of sub-state legislation. For example, the city of Berkeley in California has its own local minimum wage. We ignore these sub-state minimum wages as the smaller the geographic level at which a law was passed, the more likely that it could potentially have been created for reasons endogenous to the productivity and employment levels at a particular university.

Across the universities in our dataset and their respective years of coverage, there are 43 state-level minimum wage changes that occurred. Of those, 24 state-level minimum wage changes were increases of more than \$0.25. Following [Cengiz et al. \(2019\)](#), we refer to these as “prominent” minimum wage changes. The average prominent minimum wage event led to an increase of 8.35%. The average minimum wage faced by a lab in our sample is \$7.52.

2.3 Data Limitations

Some might wonder if the wages of undergraduate research assistants are really affected by changes in the minimum wage. While the UMETRICS data does not provide salary information for individual employees for all universities, in [Appendix D](#) we discuss how we can impute wages using labor costs associated with undergraduate workers and the hours worked by those undergraduates. Based on this

¹⁶The students in this dataset worked a relatively small number of quarters in research labs. This is because our sample for this analysis includes students who appeared in the UMETRICS employment data working at the university somewhere other than one of the research labs in our sample.

analysis, we show that approximately 35.03% of undergrads appear to earn at or below the minimum wage.

While our analysis leverages state minimum wage changes, we can also demonstrate that federal minimum wage changes appear to influence the wages of college students employed by universities by graphing the distribution of these workers' wages before and after a federal minimum wage from \$6.55 in 2008 to \$7.25 in 2009 using nationally representative data from the Current Population Survey (CPS).¹⁷ Figure A6 plots the distribution of wages of employees at universities age 18 to 22 in both 2008 in blue and in 2010 in orange. Noticeably, the distribution shifts to the right in 2010, with a clear decline in employees making below the mandated minimum wage. In addition, the distribution in 2010 shows bunching at or near the new mandated minimum wage level. This figure demonstrates that mandated minimum wage laws—even if those laws do not always cover undergraduate employees—still influence the wages paid to undergraduate research assistants.

Previous studies also indicate that university student employees frequently earn a minimum wage.¹⁸ Indeed, increases in minimum wage induce employers to switch to student and teenage employees (Lang and Kahn, 1998).

2.4 Descriptive Statistics

Figure 1 shows the effective minimum wage across universities in the sample. Figure A1 shows the distribution of price changes that occur within our sample. Many changes are less than 5%, however, a small number of large changes of more than 20% also occur in our sample. As noted earlier, we focus on minimum wage changes of more than \$0.25, following other studies such as Cengiz et al. (2019).

In addition to variation in the minimum wage level and minimum wage changes, there is considerable variation across universities in the timing of these changes. Figure A2 shows when minimum wage changes occur. The majority of these changes occur during the first quarter of the year, however, 32.56% of the minimum wage changes occur in other quarters. In Figure A3, the distribution of the length of time between minimum wage changes for universities is displayed. This plot shows that most universities experience minimum wage changes annually, although some minimum wage levels remain fixed for longer periods.

¹⁷The CPS does not provide information on the type of employment of the college students, so this sample includes all types of employment at universities. There does not seem to be a nationally representative dataset that provides information on the wages of undergraduate research assistants employed at universities.

¹⁸FLSA actually allows students to be paid 15% less than minimum wage (Freeman, Gray and Ichniowski, 1981).

Labs vary in their employment of workers of different occupational levels. In Figure A4, we show the distribution of the share of days of work done by undergraduate employees. We define labs as using undergraduate labor more “intensively” if, prior to their first minimum wage change, undergraduates accounted for more than 10% of total workdays. In Figure A5, we also display the probability of employing at least one undergrad research assistant across labs in different scientific fields for labs where the PI can be associated with a department in the UMETRICS data.

3 Empirical Strategy

We analyze the effect of minimum wage changes on four different outcomes: labor demand by university research labs, the production of scientific papers, employment of undergraduate students, and student career outcomes. Like many papers in the literature estimating minimum wage effects, we run the first three analyses using a difference-in-differences approach. For the final part of the analysis examining student career outcomes, we use an instrumental variable framework. In this section, we describe our empirical approaches, identification assumptions, and limitations.

3.1 Difference-in-Differences: Employment and Scientific Production

To estimate the effect of minimum wage changes on lab labor demand, scientific paper production, and undergraduate employment, we use a generalized difference-in-differences approach. This is implemented using the following specification:

$$E[Y_{ft}] = \sum_{j=-4}^5 \gamma_j D_{ft}^j + \mu_f + \mu_t + \delta \Omega_{ft} + \epsilon_{ft} \quad (1)$$

In this equation, the dependent variable Y_{ft} is the outcome of interest. The independent variables include D_{ft}^j , which is a variable that takes the log-difference in the minimum wage j periods in the future. We bin the end points. We also include fixed effects for the lab, μ_f , as well as the time period μ_t . The variable Ω_{ft} includes fixed effects for the time period before, during, and immediately following minimum wage changes of less than \$0.25. Following Cengiz et al. (2019), we include these controls as such small changes in the minimum wage are unlikely to impact labs in a similar manner to larger minimum wage changes.

We estimate Equation 1 with various dependent variables. When analyzing the changes in labor demand at labs, we estimate this equation using the lab-by-quarter observations from the Lab Panel

Dataset, where f represents a lab and t represents a quarter, and the dependent variable is the number of employees or days of work by employees of various occupations. When analyzing the effect on the production of science, we estimate this equation using the lab-by-year observations from the Scientific Production Dataset, where f represents a lab and t represents a year, and the dependent variable is the number of scientific publications produced by a lab within a year. Finally, when we analyze the employment of undergraduates, we use student-by-quarter observations from the Undergraduate Panel Dataset, where f represents an undergrad and t represents a quarter, and the dependent variable is whether or not the student is employed by a lab in that quarter.

As many of the primary outcomes of interest (number of undergraduate and graduate students, postdocs, and research staff employees working a lab) are discrete, we also estimate Equation 1 using a Poisson model. We replicate our results using OLS as well using indicators for minimum wage changes in the Appendix.

The effect of minimum wage changes is likely to evolve over the course of the subsequent year. Therefore, we plot the coefficients on the leads and lags of Equation 1 to trace these dynamic effects. These plots also allow us to see if the labs at universities facing minimum wage changes make employment changes in the lead up to the actual legal change. Lastly, these plots allow us to assess if the treated and control labs show parallel trends in the time period prior to the minimum wage change.

To summarize the effect of the minimum wage changes, we use the estimated coefficients from Equation 1 to compute both average effects and elasticities. Using the estimates of γ_j from Equation 1, we calculate the change in the number of employed workers within a lab between time $t = -1$ and one year later as $\Delta Q = \bar{D} * \frac{1}{5} \sum_{j=-1}^4 \gamma_j$. This equation has two components. The first is the average percentage change in the minimum wage across prominent changes in our dataset. The second is the average change in employment per quarter. This estimate reflects the percentage change in the employment of lab workers following an average minimum wage change. We also compute the elasticity of demand by removing the scaling factor: $\epsilon = \frac{1}{5} \sum_{j=-1}^4 \gamma_j$.

The generalized difference-in-differences design of Equation 1 identifies the effect of minimum wage changes by exploiting two types of variation: variation in the timing of the minimum wage changes across universities and variation in the magnitude of the changes across minimum wage increases. The main assumption of this empirical approach is that employment in labs at universities that faced a minimum wage increase at a point in time would have evolved in similar ways to the employment in labs at universities that did not face a wage change or faced different sized changes in the

same time period. By plotting the event-study coefficients from Equation 1, we document that treated and untreated university labs exhibit parallel pre-trends, which support this assumption. In addition, the timing of the minimum wage changes are unlikely to be associated with some unobservable that would influence the evolution of employment at one university versus another since these changes are dictated by state legislatures for all employers in a state.

There are a few threats to the causal interpretation of our analysis based on the above specifications. First, the identifying assumption of the generalized difference-in-differences setup is that changes in employment for labs at universities that faced no minimum wage change or small minimum wage changes predict the counterfactual path for employment in labs at universities that faced larger minimum wage changes. If labs in states that had large minimum wage increases are systematically different than labs in states that had smaller or no minimum wage increases, then these groups may not be suitable counterfactuals.¹⁹ Table A5 compares the attributes of labs that faced smaller and larger minimum wage changes over the course of our sample period. The results in that table demonstrate that, despite statistically significant differences, the labs in these two groups appear economically similar on many dimensions, although labs that faced larger minimum wage changes also tended to be larger labs more generally. By including lab fixed effects, we control for the time-invariant differences in lab size, for example due to differences in the fields of the labs.

Second, if the minimum wage in a state is adjusted in response to the productivity or organizational changes within university labs, then the results would be biased due to endogeneity. This seems unlikely for a variety of reasons. Most of the universities studied in our sample make up a relatively small share of their respective state's overall employment. While some universities are located in cities or counties that have minimum wage rates that are distinct from their state minimum wage, for those universities, we perform our analysis using the state minimum wage.²⁰ This is because the state minimum wage is still likely to impact employment at university labs, and yet the state wage is less likely to be driven by employment at those universities.

Third, given that minimum wage changes occur in a staggered fashion across the labs in our data, one might wonder if the issues identified by Meer and West (2016) and Goodman-Bacon (2018), where negative weighting arises when treatment effects vary over time, influence estimated effects. In order

¹⁹For example, if states that implemented larger minimum wage changes also provided funding increases to university labs that exceeded the trajectory of those given to labs in states with smaller minimum wage changes.

²⁰Berkeley, California is an example of a city with a sub-state minimum wage.

to address any concerns about the how the weights of the staggered setup may be impacting our results, we leverage the “stacked” approach of [Cengiz et al. \(2019\)](#). The advantage of this approach is three-fold: We remove so-called “forbidden comparisons” by excluding labs at universities from the control group; We are able to estimate the effect using Poisson regression as our dependent variables are often non-negative counts; We can estimate the effect with labs that face multiple minimum wage treatment events across our sample panel. Two caveats should be noted. First, this approach assumes that a lab’s potential outcomes for a current change in the minimum wage does not depend on anticipation of future minimum wage changes. This assumption, however, may not be restrictive in this context, since many decisions made by labs are on a short-term horizon: employment decisions likely revolve around the turnover of students within an academic year and grants last for limited period. Furthermore, we restrict our attention with regard to employment changes to the one year following minimum wage changes. Second, the aggregation of estimates across stacks will be weighted in proportion to the number of treated units within each event-stack as well as the variance of the treatment [Roth et al. \(2023\)](#). While this may be somewhat opaque, our main goal with this approach is to confirm the robustness of our results even after removing problematic comparisons. The consistency of results across these empirical approaches and the additional leverage from utilizing variation in the magnitude of the minimum wage changes gives us confidence in the direction of the effects.

Lastly, one might wonder why we take a generalized difference-in-differences approach instead of alternative empirical frameworks used in the past to analyze the minimum wage, including leveraging bordering counties ([Dube, Lester and Reich, 2010](#)) or using federal minimum wage changes as an instrument ([Card, 1992](#); [Baskaya and Rubinstein, 2012](#)). Those approaches require large numbers of firms operating near the border of counties or in states with minimum wages below the federal minimum wage. Our data includes a limited number of universities, with some in the same states ([The Institute for Research on Innovation & Science, 2022b](#)). In addition, the universities in our dataset almost all come from states in which the federal minimum wage does not bind. Therefore, we are unable to get statistical power using these previous methods. Instead, we believe that our approach allows us to leverage the richness of our data, by utilizing variation in the timing and magnitude of minimum wage changes across thousands of universities labs. Moreover, recent work has emphasized the advantages of generalized difference-in-differences and event study designs for estimating the impacts of the minimum wage, particularly in settings with staggered treatment timing and heterogeneous treatment effects ([Dube and Lindner, 2024](#)).

3.2 Instrumental Variable Analysis of Student Career Outcomes

We next examine how students' research experience in university labs affects their subsequent career outcomes, focusing in particular on whether they pursue a graduate degree or enter a scientific career. A key challenge in interpreting this relationship is that the amount of time students spend working in labs is likely endogenous. For instance, students who already intend to pursue a doctoral degree may be more likely to seek out lab positions to strengthen their graduate school applications or build relationships with faculty. Conversely, students with substantial financial need, such as those with limited aid packages, may work more hours on campus regardless of their interest in science careers.

To address these concerns, we exploit variation from changes in the minimum wage that occur while students are enrolled in college. These changes affect the likelihood that undergraduates work in research labs, independent of other factors such as their underlying career aspirations. We use these policy changes as an instrumental variable for lab employment, providing exogenous variation in research experience among otherwise similar students. This allows us to estimate the causal effect of (paid) research experience on educational and career outcomes. Specifically, we estimate the following two-stage least squares regressions:

$$E[Exper_i] = \pi MWageChanged_{jt} + \mu_j + \mu_t + \delta\Omega_{it} + \epsilon_i \quad (2)$$

$$E[CareerOutcome_i] = \beta Exper_i + \mu_j + \mu_t + \delta\Omega_{it} + \epsilon_i \quad (3)$$

In the above equations, i represents an individual undergraduate student, t represents the cohort of the undergrad (defined by the year they graduated from college), and j is the university where the undergrad received their bachelor degree. The variables μ_j and μ_t represent fixed effects for the university and cohort, while Ω_{it} is a collection of additional attributes of the individual and their university.

Equation 2 is a first-stage regression. In this specification, we regress the time that an undergrad spent employed in a research lab during college, $Exper_i$, on $MWageChanged_{jt}$, which represents if the minimum wage changed during the four years when students of cohort t at university j would have been studying and working. We estimate this first-stage regression two ways. First, we estimate the model with $MWageChanged_{jt}$ as a single indicator variable, which is one when the minimum wage changed during the student's years in college. We also estimate this first-stage with $MWageChanged_{jt}$

as four indicator variables representing if the minimum wage changed during each of the respective years that the student was in college.

Based on our analysis of labor demand by labs as well as the first-stage regressions, instrumenting for a student's time working in a research lab with changes in the minimum wage satisfies the inclusion condition. In addition, since state legislatures are unlikely to take into account the employment of undergrad research assistants when considering the enactment and the timing of minimum wage changes, this instrument seems likely to satisfy the independence assumption. In addition to regression evidence, we also show non-parametric evidence of both the first-stage and the reduced-form in Appendix E.

For the exclusion restriction to hold, changes in the minimum wage during a student's time in college must affect their decision to pursue a graduate degree or a scientific career only through the channel of their research experience in university labs. One potential violation of the exclusion restriction arises if minimum wage increases change the composition of students working in labs, and thus the sample used in our analysis. For example, if higher-achieving students become more likely to work in labs following a minimum wage increase, then doctoral enrollment rates could increase regardless of lab work experience.

Another possible violation could occur if higher minimum wages directly affect students' financial circumstances, making graduate education more accessible and thereby directly affecting enrollment decisions. Alternatively, if minimum wage hikes alter the responsibilities or working conditions of graduate students in ways that make doctoral programs less attractive, undergraduates may be less inclined to pursue such paths, regardless of their lab experience.

Although we do not directly observe students' academic records or socioeconomic backgrounds, we account for potential compositional changes using a rich set of control variables, as described in Appendix F.

4 Results

4.1 Effect on Labor Demand

Figure 2A plots the event study coefficients from estimating Equation 1 around minimum wage changes. Each line represents the estimates when the dependent variable is the number of days that different types of labor (undergrad, graduate student, postdoc, and staff) are employed in labs. The plotted coefficients are scaled by the size of an average prominent minimum wage change (8.4%). In

the quarters prior to the minimum wage change, the coefficients are not statistically distinguishable from zero.²¹ In the quarters following the minimum wage change, the use of undergraduate labor decreases significantly. For example, the coefficient for one quarter after a minimum wage translates to a 7.5% decrease in undergrad days employed.

In contrast, the use of graduate student time increases on average after the minimum wage change. While graduate students are frequently employed as research assistants on the basis of department fellowships rather than lab-specific funds, and thus would not be included in our dataset, any time billed specifically to the lab's accounts would be included. One quarter after a minimum wage change, the average lab increased their use of graduate labor by 11.1%.

Postdoc labor remains largely flat during the time before and after the minimum wage change. Postdocs are typically paid according to rates set by a university or funding agencies, and postdocs tend to do work that is different from undergraduate research assistants in a lab. Therefore, it would be surprising if postdoctoral employment changed after a minimum wage change. There is a small decline in employment of staff, on the other hand, although the coefficients are not significantly different from zero except for 4 quarters after the minimum wage change. We note there is no significant overall effect on employment for all four types of labor combined.²²

Figure 2A demonstrates a number of important results. First, the relatively flat pre-trends show that even though many minimum wage changes are known well in advance, PIs do not appear to make large adjustments in anticipation. Second, the effect of the minimum wage is primarily seen in the reduction of the lowest paid workers, namely undergraduate research assistants and, to a lesser extent, research staff. Third, the small but visible increase in graduate student labor suggests possible substitution effects, with graduate students perhaps taking on more of the work that undergrads and research staff did previously following the minimum wage change.

Are labs reducing the amount of work they are giving to undergraduate research assistants or are labs decreasing the number of undergraduate workers they employ? Figure 2B plots the scaled coefficients from estimating Equation 1 with the dependent variable of the number of distinct workers employed in an occupation. Similar to Figure 2A, the plot demonstrates that the number of undergraduate employees declines during the year after the minimum wage change. In contrast, the number of graduate students trends upwards, although not significantly so in any quarter. This plot shows that

²¹At the 5% level.

²²The estimated coefficient for all four types of labor is -0.006 and the standard error is 0.015.

a portion of the decrease in the days worked by undergraduates is coming from employing fewer undergraduates in labs.

The reduction in the employment of undergraduate research assistants could be due to changes on the intensive or extensive margins. On the intensive margin, labs with many undergrad workers might decide they get by with fewer RAs. On the extensive margin, smaller labs might decide to forgo hiring an undergrad RA at all.

Figure 3 plots the scaled coefficients from Equation 1 when the dependent variable is an indicator for a lab employing at least one worker in an occupation and the equation is estimated with OLS. The line for employing an undergraduate shows a marked decline in the year following the minimum wage change. Specifically, a quarter after the minimum wage change, the probability of employing an undergraduate in a lab decreases by 2.9 percentage points relative to the quarter prior to the minimum wage change on average. The employment of graduate student workers ticks up slightly over the course of the same time period. The employment of postdocs and research staff again show little movement.

This figure demonstrates that a large portion of the effect on undergraduate labor is a result of changes in labs that are on the margin of employing undergraduates. The pronounced decline in the probability of employing any undergraduates in this figure demonstrates that these labs, following the minimum wage change, tended to not employ any undergrads.

Table 2 summarizes the event-study plots by estimating ΔQ and ϵ with Equation 1. Columns (1) and (2) present estimates for the impact on days of undergraduate employment and the number of distinct undergraduate employees, respectively, corresponding to Figure 2A and Figure 2B. Column (3) shows the results from the LPM model for if the lab employs at least one undergraduate, corresponding to Figure 3. These estimates are all negative and significant, confirming the results evident in the figures, and show the most of the impacts of the minimum wage appear to be on the extensive margin.

Meanwhile, Column (4) and (5) turn to the intensive margin, with Column (4) showing the estimates for the number of days per employee who remain employed in the lab, and Column (5) showing the the number of days of undergraduate employment for the labs that continue employing undergraduates after the minimum wage change. In both cases, the coefficients are not significant, and suggest that the majority of the movement following the minimum wage changes occur on the extensive margin, while the intensive changes are less pronounced.

The magnitude of the estimated elasticities in Columns (1)–(3), while large, are not entirely uncommon within the minimum wage literature (see e.g. [Brown and Hamermesh \(2019\)](#)). As shown in [Dube and Zipperer \(2024\)](#), the estimated elasticity of demand for lower skilled workers, such as teens, in previous studies tends to be larger than for more skilled groups. For example, [Jardim et al. \(2022\)](#) find elasticities around -1.0 in the short-run for low wage workers. For undergrad workers in labs with budgets fixed in the short-term, the relatively high elasticity is therefore not entirely surprising.

While we cannot compute the own-wage elasticity discussed in the recent minimum wage literature by [Dube and Zipperer \(2024\)](#) for our entire sample due to lack of wage data for all universities, we are able to estimate the OWE using imputed wages for a subsample of the data. In Appendix D, using a sub-sample of our data in which we can impute both labor costs associated with undergraduate workers and the hours worked by those undergraduates, we find an own-wage elasticity of -0.469. This estimate falls squarely within the range found for other lower-skilled workers, which [Dube and Zipperer \(2024\)](#) refer to as “medium negative” relative to other minimum wage studies.

4.2 Heterogeneity across labs

In Table 3, we examine heterogeneity in the effects of minimum wage changes by estimating Equation 1 separately for different types of labs. Columns (1) and (2) present results for labs categorized as “not-intensive” and “intensive” in their use of undergraduate research assistants, respectively. We define a lab as “intensive” if, prior to its first minimum wage change, undergraduates accounted for more than 10% of total workdays; labs below this threshold are “not-intensive”.

The estimated change in undergraduate labor usage for not-intensive labs is small and statistically insignificant. In contrast, intensive labs experience a substantially larger and significant reduction in undergraduate employment. We further confirm this pattern by re-estimating the event study specification (Equation 1) separately for intensive and not-intensive labs and plotting the resulting coefficients in Figure 4.

These findings are consistent with the idea that labs that rely more heavily on undergraduate labor are more sensitive to changes in increases in labor costs, while labs that make minimal use of undergraduate assistants are largely unaffected by such wage increases.

In Columns (3), (4), and (5) of Table 3, we restrict the sample to the fields of Biology, Physics & Engineering, and Psychology respectively. In Columns (5) and (6), we restrict the sample to labs funded by NIH and NSF respectively. These estimates show that biology and labs funded by NIH

are more sensitive to the change in the minimum wage, while NSF-sponsored labs are less so. This could be because of differences in the way that undergrad work contributes to these labs or because of differences in funding agency policies regarding supplements and cost adjustments.

Columns (7) and (8) restrict to labs with grants that have fewer than two years of remaining expenditures to them and those labs with grants having more than two years left. Both coefficients are significant statistically and negative, indicating that labs are elastic in their demand for undergraduate labor regardless of where they are in the life cycle of their funding.

Overall, the pattern of heterogeneity suggests that labs that rely more heavily on undergraduate research assistants, such biology and psychology labs, are particularly affected by increases in labor costs. Additionally, our results indicate that some funding agencies may offer greater flexibility in addressing these cost increases than others.

4.3 Substitution to Graduate Labor

To what extent is there substitution with graduate student labor following minimum wage changes? In Table 4, we examine this by estimating Equation 1 using the number of days of graduate employment as the dependent variable. In Column (1), we find a positive and significant ΔQ , 6.9, indicating that indeed there is an uptick in the number of days of graduate work in labs following minimum wage changes. In contrast, Column (2) displays the results when regressing the number of distinct graduate students on the minimum wage changes. While we find a positive coefficient, the coefficient is not statistically significant. These results indicate that the time that grad students work in labs increases, but the number of distinct grad student employees does not change significantly. This is plausible since adjusting the number of grad students working in a lab is challenging in the short-run and likely to only occur at the beginning or end of an academic year.

In Columns (3)–(6), we estimate Equation 1 for graduate student labor, splitting the sample between universities with and without graduate student unions. We find that both types of institutions exhibit a similar uptick in graduate student employment following minimum wage increases. This result is somewhat surprising: one might have expected less substitution toward graduate labor at unionized schools, where collective bargaining agreements could restrict the reallocation of tasks previously performed by undergraduates. However, it is also possible that universities with graduate student unions are those where graduate workers are already more central to lab operations, and the

observed increase simply reflects their importance in these settings.²³

The results above highlight that when the cost of lower skilled labor increases, higher skilled labor, such as graduate students, may be called upon to perform tasks typically done by lower skilled workers. If these graduate students are time constrained, additional tasks may impact their training and career progression.

4.4 Robustness

Aspects of both the setting and the econometric specifications may influence the estimated effects. Therefore, in this section we demonstrate the robustness of our analysis.

First, funding for labs typically comes in the form of grants with set start and end dates. If a minimum wage change coincides with a grant's expiration, this could induce a spurious correlation between minimum wage changes and lab employment. To address this concern, Table 5 adds control variables to Equation 1 indicating whether a grant supporting the lab was in its first or final quarter. These fixed effects account for potential ramp-up or wind-down periods. Columns (1)–(3) show that our estimates remain similar to those in Table 2, suggesting that the funding life cycle is not driving the observed results.

Second, universities may exhibit different seasonal employment patterns. For example, schools on quarter systems may have different hiring cycles than those on semester systems. If minimum wage changes correlate systematically with these patterns, our estimates may be biased. In Columns (4)–(6), we include university-specific fixed effects for each quarter of the calendar year, as well as for a lab having a grant beginning or ending in a quarter. The overall pattern of results remains similar, though the estimated magnitudes are somewhat attenuated, and the effect on the number of distinct undergraduate employees becomes statistically insignificant.

Third, universities may follow different long-term employment trajectories—some increasing undergraduate involvement in research, while others reduce it. If these trends are correlated with minimum wage policies, they could bias our estimates. To account for this, Columns (7)–(9) add separate time trends for each university. Again, we include the fixed effect for the lab having a grant beginning or ending in a quarter. The results are not fundamentally different.

Fourth, recent advances in the staggered difference-in-differences literature highlight the importance of treatment heterogeneity and the risk of misleading comparisons in two-way fixed effects

²³Appendix Table A7 reports mean characteristics of lab-by-quarter observations for universities with and without graduate student unions.

(TWFE) and event study models (Meer and West, 2016; Goodman-Bacon, 2018; Roth et al., 2023). While our main specification (Equation 1) leverages variation in both the timing and magnitude of minimum wage changes with repeated “treatment” events, we take additional steps to guard against potential biases from improper comparisons or negative weights.

Specifically, we implement a “stacked” event study design following Cengiz et al. (2019) and the methodology described in Wing, Freedman and Hollingsworth (2024). For each prominent minimum wage change in a state, we create a “stack” with the observations from our Lab Panel dataset for labs at universities in that state as the treated labs along with labs at universities that did not experience a prominent minimum wage change within one year of the focal event as the control labs. By removing those labs that experienced a prominent minimum wage change during the same time-window, we exclude so-called “forbidden comparisons”. By combining those individual event stacks together, we create a dataset that we refer to as the Stacked Dataset. We then re-estimate Equation 1 using that Stacked Dataset, including event-specific lab and quarter fixed effects, and display the results in Figure 5 and Table 6. As the pattern of the results are consistent with our main results, we believe that this provides evidence that our findings are not driven by forbidden comparisons or negative weights.

Fifth, one might wonder if our results may be influenced by mean reversion around the time of minimum wage changes. For example, Figure 2A suggests that lab employment may dip in the quarters preceding a minimum wage increase.²⁴ We address this concern by showing that our results hold even if we add the trend of the outcome from prior to the minimum wage changes, following the procedure of Derenoncourt, Noelke and Weil (2021). Using our stacked dataset, we estimate a linear time trend in the days of employment for undergraduate workers during the period prior to the minimum wage change. Then we add this linear trend coefficient to the estimated dynamic effect coefficients from the full model. As shown in Appendix J and Figure A11, the effect remains consistent and significant.

Lastly, our primary analysis is conducted at the lab level, under the assumption that principal investigators (PIs) have flexibility in allocating funding across grants. However, if our mapping of grants to labs is imperfect, this could affect the estimated treatment effects. In order to demonstrate that this is not a concern, we re-run our main analysis using a grant-by-quarter panel as well.²⁵ The

²⁴Note that this pre-treatment pattern is not present when using a traditional event-study style difference-in-differences regression using indicators, shown in Figure A8, rather than the generalized version using changes in the minimum wage.

²⁵Summary statistics for this Grant-by-Quarter Panel Dataset are shown in Table 1 Panel C.

results of this analysis are shown in Table 7. The estimates in this table show a similar pattern to the lab-level analysis and reinforce that the lab definitions do not drive the estimated impact of the minimum wage changes on lab-level employment outcomes.

Taken together, these robustness checks suggest that our findings are not artifacts of model specification, university-specific trends, or the structure of research funding. Rather, they reflect a robust relationship between minimum wage increases and changes in student employment.

4.5 Scientific Productivity

The previous sections show that changes in the minimum wages can have significant effects on the employment of undergraduate research assistants and research staff. In this section, we explore what impact those labor cost changes ultimately have on the production of scientific research. Because it is challenging to associate a scientific publication with the specific quarter in which the scientific work was done, we estimate the models in this section using lab-by-year data.

Table 8 shows the estimates of Equation 5 when the dependent variable is the number of publications associated with the lab in a year.²⁶ Column (1) uses the number of WoS publications associated with the lab in the year, Column (2) uses the number of PubMed publications, and Column (3) uses the citation weighted number of WoS publications in the year using five-year forward citations. Across all of the specifications, the coefficients are small and not statistically significant.²⁷

We believe that this implies that while there may be some adjustment costs due to changes in the minimum wage, the overall effect on scientific production is likely to be minor in the short-run. These results are also consistent with the substitution to graduate labor that we observed earlier. More research will be required to understand if the changes in the personnel working in labs also impacts the rate and direction of research projects undertaken.

4.6 Aggregate Effects and Relocation

The impact of minimum wage changes on research labs depends, in part, on whether labs can secure additional funding to offset higher labor costs or shift some work to collaborators in lower-wage states. In this section, we examine whether there is evidence that principal investigators (PIs) adopt either of

²⁶Note that we use Equation 5 rather than Equation 1 here because we do this analysis at the annual level.

²⁷In Table A13, we repeat this analysis regressing the number of publications on the log-transformed minimum wage for labs with fixed effects for the year and lab. This more traditional two-way fixed effects setup also shows no statistically significant effect on production of papers.

these strategies.

In Table 9, Column (1), we estimate Equation 1 with a dependent variable of the number of grants that a lab has funding it in a quarter. Column (2) estimates the same equation but with a dependent variable of the log of total dollars of spending by the lab. Column (3) is the log of total labor cost as the dependent variable. Across all three specifications, the estimated coefficients are not significant. This implies that in the short-run, PIs are not increasing the number of distinct funding sources that they have or the total amount of funding that they have to spend. In addition, these results imply that the amount budgeted for labor costs versus other costs is also somewhat fixed in the short term.

Column (4) of Table 9 shows the estimates from a linear probability model with a dependent variable of whether the lab has funding from a grant labeled as a supplement. Lab PIs may be able to request supplementary funds from certain funding agencies because of additional scientific work that they wish to conduct or in order to handle increased costs. The estimate is positive and statistically significant at the 10% level. Relative to the sample mean, this coefficient implies a 8.46% in having supplemental funding for the lab. This implies that on average labs may apply and even receive some supplemental funding in the short-run.

Column (7) repeats this analysis for the sub-sample of labs that are funded by NIH grants. NIH specifically allows grantees to apply for supplements for their grant amount under certain conditions.²⁸ The estimated coefficient on the probability of a supplement in the quarters following the minimum wage change increases by 0.5 percentage points or 27.72% relative to the sample mean.

We also test if PIs are relocating the scientific work for their lab to collaborators in other states when the minimum wage increases in their state. We test for this in Column (5) by examining if the total amount of dollars subawarded (provided from a primary grant to a collaborator) increases follow a minimum wage change. We find a negative and insignificant coefficient.

We also test if the subaward money is more likely to be sent to labs in locations with lower minimum wage levels following a minimum wage change. For this analysis, we use a dependent variable of the dollars of subaward funds weighted by the minimum wage in the state for which the subaward is being sent. If the coefficient on this was negative that would indicate that subaward dollars are being sent to places with lower minimum wage rates. Column (6) shows the estimated coefficient, which is again, not significant.

We interpret these results to mean that PIs either have limited options in changing their subaward

²⁸<https://grants.nih.gov/funding/funding-categories/supplemental-funding>

allocation after the start of their awards or are not using this mechanism in the short-run.

4.7 Reallocation

In this section, we explore movement of workers across labs in response to the minimum wages changes. The recent minimum wage literature has pointed to such “reallocation” effects as an important mechanism by which labor markets adjust to the higher wages facing employers, by re-allocating labor to the higher productivity firms (Dustmann et al., 2021). In this case, since undergraduate research assistants are both labor inputs and an output of the lab, the expected effects on reallocation are more ambiguous. If minimum wage changes affect which labs employ undergraduate research assistants, it might change the experience and training that these individuals receive. If the most productive labs are the first to cut undergraduate research assistants because they are focused solely on production and not training, then the experience of undergraduates who continue to work in labs will be different than if the high productivity labs continued to employ undergraduates.

Our previous results demonstrated that following a minimum wage increase, labs decreased their use of undergraduate labor. In this section, leveraging our unique dataset on all sponsored research at the universities in our sample, we examine if those undergraduates find other opportunities to be involved in research activities. Table 10 shows estimates based on the Undergraduate Panel Dataset. Specifically, we regress an indicator for if the undergraduate is employed in any lab in our sample on an indicator for if the university that the undergrad attended experienced a minimum wage change. The regressions also include fixed effects for each individual undergraduate as well as their cohort, defined as the first year that we observe that student being employed in our data.

Table 10 Column (1) shows that the probability of being employed in a lab decreases by 5.6 percentage points or 13.2% relative to the mean of the sample. In Column (2), we include controls for the experience of the undergraduate in a lab, which we measure as the number of prior quarters that the undergrad has been employed in a lab. We also include the interaction of the minimum wage change and the experience of the undergrad. These estimates show that students with more experience are less likely to be employed. The reason for this negative association is because we do not observe when the student graduates; therefore, in the later observations, the student is less likely to be employed as they are more likely to have already graduated. The interaction term between experience and a minimum wage change is positive. This implies that undergraduates with more experience working in scientific research are also more likely to continue working in labs when the minimum wage changes.

In Column (3), we include an interaction term between a minimum wage occurring and the undergraduate being female. The interaction term tells us if female undergraduates leave research assistant positions at a differential rate following the minimum wage changes. The estimated coefficient is small and not significant implying that the effect on the rate of working in a lab is similar for men and women undergraduates.

Column (4) includes an interaction term indicating whether the undergraduate student was ever paid from an account associated with the Federal Work-Study (FWS) program. The positive and significant coefficient on this interaction suggests that FWS students are more likely to continue working as research assistants following a minimum wage increase. This may reflect the fact that FWS subsidizes the cost of employing these students, making them less costly to retain for research labs.

For students who remain employed in a lab, they may not remain in the same lab. [Dustmann et al. \(2021\)](#) demonstrated that workers reallocated towards higher productivity firms following minimum wage increases. We explore a similar dynamic within universities. Specifically, we examine if the students who remain employed tend to work in higher productivity labs.

To operationalize this, for students employed in a lab, we estimate the two-way fixed effect model with the dependent variable as the number of publications in PubMed produced each year by the lab employing a student relative to other labs at the same university and in the same field.²⁹ Thus, the dependent variable is a z-score. As before, we include fixed effects for the individual student and the cohort year. We estimate this model using the subset of observations from the Undergraduate Panel Dataset where the undergrad is employed by a lab.

Column (5) displays the estimated coefficient. The positive coefficient on the minimum wage changing indicates that students who remain employed may have worked in labs that produce relatively more papers per year than the labs that they had worked in prior to the minimum wage change, however, this coefficient is not significant.

We also investigate if students who remain employed flow to smaller or larger labs. To operationalize this analysis, we take the z-score of the number of undergrads employed in a lab within an institution in each year as the dependent variable. The positive and significant coefficient implies that undergrads who remain employed are more likely to work in larger labs, employing relatively larger numbers of undergraduate employees. Consistent with our finding on the importance of the extensive margin in Figure 3, smaller or marginal labs may be more likely to drop undergraduate research

²⁹Note that when the field of the lab is not available, we pool those labs together and standardize with an “Unknown” field.

assistants following minimum wage increases.

These results highlight that the impact of the minimum wage changes on the exposure of undergraduate students to scientific research is both significant and not uniform. First, labs are less likely to employ RAs, and the undergrad students are less likely to find alternative labs to work in. Second, minimum wage changes are more likely to impact students early in their undergrad years than those with more experience. Third, students with federal work study support may be less impacted, which implies that students from less affluent backgrounds may be partially shielded. Finally, students who continue to be employed are in larger labs and may be in labs that produce more scientific publications.

4.8 Effects on Student Careers

In this section, we examine how minimum wage changes affect student trainees' exposure to scientific work in university labs and their subsequent career choices using data from the Student Outcomes Dataset.

Column (1) of Table 11 shows the relationship between the time an undergraduate works in a lab, measured in quarters, and the likelihood of pursuing a doctoral degree when controlling for the student's undergraduate institution and year of college graduation.³⁰ The estimated coefficient of 0.010 is statistically significant and implies that working one more quarter is correlated with a 5.9% higher rate of enrolling in a doctoral-level program relative to the unconditional mean in this sample.

Columns (2) and (3) provide first-stage regressions from Equation 2 for our instrumental variable approach. In these models, we regress the number of quarters a student worked in a lab on whether or not the minimum wage increased during their undergraduate years or binary variables for if the minimum wage changed in each of the four years a student was in college. In Column (2), the estimated coefficient on the minimum wage changing is -0.26 and significant, implying a 18.1% reduction in the time worked in a lab during college. This is consistent with our previous results showing that labs decrease their use of undergrad labor when the minimum wage increases. The *F*-statistic on this model is 25.88, which indicates that this instrument is unlikely to be considered a weak instrument. We also estimate a first-stage model with separate instruments for if the minimum wage changed in each of the four years a student was in college. The estimates in Column (3) show negative and significant coefficients for the indicators of minimum wage increases during students' first and second

³⁰We sum the total number of months in which the student worked in a lab and divide by three to calculate quarters of work.

years. The estimated coefficient on the minimum wage change in the third and senior year of college are negative but not statistically significant. The F -statistic on this model is 59.34.

Columns (4) and (5) show the reduced-form regressions for these instruments. Again, the single instrument version in Column (4) shows a negative, although not statistically significant, coefficient. The multi-instrument version in Column (5) shows negative coefficients for the first three years of college, although only statistically significant in the first and second year, and a positive coefficient in the final year. On the whole, these imply a somewhat negative association between minimum wage increases and the probability of pursuing a doctoral-level program.

The patterns in Table 11 Columns (2)-(5) are confirmed in Figure A7, where we show the first-stage and reduced-form evidence non-parametrically. In those figures, after residualizing by university fixed effects, we plot the mean quarters worked in a lab for students who experienced a minimum wage change during their college years versus those who did not. We plot this for each cohort of students based on their year of graduation. While the plot is somewhat noisy, in the majority of the years, students who experienced a minimum wage change were employed for fewer quarters in labs than those who did not experience that change. We also plot the probability of pursuing a doctoral degree by graduation year, again comparing exposed and unexposed students to minimum wage changes. Although the gap is not present in every year, the overall pattern shows that students who experienced a minimum wage change were less likely to pursue doctoral-level education.

Table 11 Columns (6) and (7) show the 2SLS estimates for the effect of time working in labs on pursuing a doctoral degree using the single instrument and the four binary instruments, respectively. The estimated coefficients for the time worked in a lab are 0.070 and 0.103 with both statistically significant. These models imply that working an additional quarter in a university research lab increases the probability of attending graduate school by 7.0-10.3 percentage points. Relative to the unconditional probability of enrolling in a doctoral program, these estimates suggest a 41.22 - 60.46% increase in the rate of pursuing doctoral programs. The p -value of a test of the overidentifying restrictions, the Hansen's J -statistic, using these four instruments is 1.13 (p -value of 0.771). Therefore, we do not reject the validity of these instruments.

While minimum wage changes may appear modest, our results suggest that these shifts in labor costs can have meaningful effects on the pipeline of future scientists. The reduced-form estimate in Table 11, Column (4), indicates that experiencing a minimum wage increase during college reduces the probability of pursuing a doctoral degree by 1.8 percentage points. Given our sample of 28,283

students, this implies that if all students had experienced a minimum wage increase, roughly 500 fewer undergraduates in our sample would have pursued these advanced degrees.

Table 12 repeats the same exercise but with the outcome of whether or not a student is later employed in the life sciences industry. The results of the 2SLS models in Column (6) and (7) are 0.024 and 0.018 and significant at the $p < 0.01$ level. These results imply that an additional quarter of time working in a university lab translates into a small change in the probability of working in the life sciences, although relative to the very small unconditional probability of 0.03, this is a meaningful increase.

We next examine a specific type of scientific career outcome: employment in the life sciences industry. The life sciences sector is often a desirable career path for students trained in research-intensive environments, especially in areas aligned with federally funded biomedical research. Given the central role that the National Institutes of Health (NIH) plays in funding life sciences research at universities, we next explore whether experience in NIH-funded labs is particularly predictive of entry into this sector.

Table 13 repeats the above IV exercise with the outcome of being employed in life sciences industry, but replaces the endogenous variable with the number of quarters worked in a lab funded by the NIH. Column (1) shows that the association of NIH lab experience with the outcome of going into life sciences employment is small, but statistically significant. Columns (2) and (3) show the first stage regression. Both the single instrument version and the set of indicators show a similar pattern to the previous results with minimum wage increases being associated with working fewer quarters in these labs. As with the above results, the effect is most pronounced when the minimum wage increase occurs in the first two years of college. The F-statistic on the single and multiple instrument first-stage regressions are 29.54 and 161.58. Columns (4) and (5) show reduced-form evidence. Finally, Columns (6) and (7) show the 2SLS results. The estimates for the single and multiple IV models are 0.022 and 0.020 and significant at the $p < 0.01$ level. These estimates again highlight that additional time spent working in labs funded by NIH increases the probability that undergraduate students work in the life sciences after graduation.

Overall, our findings reveal that spending more time working in research labs does affect the career trajectories of the students in our sample. Specifically, it can increase the rate that students go on to doctoral programs or working in the life sciences. The results are notable because all of the students in our sample worked at their university in some capacity during their college years. Therefore, one might have thought that the decision of whether or not to pursue doctoral studies or

careers in science would be largely driven by that selection. Instead, our estimates reveal that these choices are partly influenced by additional exposure to scientific work as research assistants.

This analysis has several limitations, and our findings should be interpreted with caution. First, because our undergraduate data come from lab employment records, our sample includes only students who have worked at their university in some capacity. As a result, our analysis examines the effect of spending more or less time in a lab among this group, rather than the broader impact on all undergraduates who might consider lab work. Specifically, we are unable to identify the extensive margin: the effect of lab employment across the entire undergraduate population.

Second, because our data are anonymized, we have limited information about the students themselves. We do not have access to their academic performance, major, or socioeconomic background, preventing us from exploring how these factors influence the relationship between lab experience and doctoral degree attainment.

Despite these data limitations, we perform a number of robustness and placebo analyses providing support for the validity of our instrumental variable approach. For the instrumental variable analysis to be valid, minimum wage increases must affect students' career outcomes, such as enrolling in a doctoral program, only through their impact on employment in labs. There are several potential threats to this exclusion restriction.

First, minimum wage increases are correlated with economic downturns. Therefore, economic downturns could spuriously instigate states to increase their minimum wage and induce students to pursue advanced degrees. Given our difference-in-differences setup, however, we are able to control for the wider economic conditions. Therefore, conditional on the time fixed effects, we do not believe that such a spurious correlation may be impacting our results.

Second, minimum wage increases could change the composition of students working in labs (e.g., attracting higher-achieving students). For example, if academically stronger students begin working in labs because of the higher pay, we might expect higher rates of attending doctoral programs. We do not have direct data on students' academic performance. In Appendix F, we attempt to control for some of these compositional factors using data, such as whether or not the student's self-reported bachelor's degree information indicates that the student graduated with honors. Given that the magnitude of the IV coefficients remain stable when adding controls, that analysis indicates that compositional changes are unlikely to impact our findings regarding the effect of exposure to scientific work on pursuit of a doctoral-level degree. That being said, the data available to us, such as whether or not

a student achieved academic honors, may also be caused by working in lab. Therefore, we caution over-interpreting those results.

Third, minimum wage increases could affect students' financial situations directly, making advanced study more or less feasible. If the change in minimum wage directly changed the financial standing of students, this could also violate the exclusion restriction. For example, if undergrads can pay off more of their student loans, this might shift their view of the feasibility of graduate programs regardless of the actual experience that they have working in a lab. Given the magnitude of student loans and the relatively small scale of most minimum wage increases, we think that this is unlikely to bias our results. On average, the prominent minimum wage events increased the nominal wage by 8.35% and students worked 1.44 quarters. If we assume students worked 10 hours a week at the wage of the average state minimum wage at the time of prominent increases in our data (\$8.95), this would only translate into an increase of approximately \$129.14 by the end of their college years, which seems too small to significantly impact their decision through this channel.

Fourth, the minimum wage increases may make applying for minimum wage jobs more appealing than pursuing graduate school. While one would need data on whether or not students graduating with bachelor's degrees consider minimum wage positions versus graduate school, the median weekly earnings of individuals with a college education implies a significantly higher hourly wage than the minimum wage.³¹

Fifth, minimum wage increases could alter the nature or appeal of doctoral programs themselves, perhaps by shifting graduate students' responsibilities or funding conditions. If minimum wage increases change the work of graduate students in doctoral-level programs, undergraduate students may find it less appealing. In Table 4, we do find that following minimum wage increases, graduate students may be doing more compensated work within labs. This raises a potential concern for the exclusion restriction: if undergraduate students perceive this shift in graduate student responsibilities as making doctoral programs less appealing, it could influence their decision to pursue a PhD independently of their own lab experience. However, it is important to note that our evidence on graduate students taking on more work is specific to the universities where the minimum wage increased. In

³¹The federal minimum wage is \$7.25/hour, which at 40 hours a week would translate into \$290 per week. The median weekly earnings of individuals with just a college degree is \$1,541, which at 40 hours a week would be \$38.53/hour. <https://www.bls.gov/opub/ted/2024/median-weekly-earnings-of-full-time-workers-with-only-a-bachelors-degree-1541-in-q2-2024.htm>

contrast, our measure of doctoral program enrollment reflects where students attend graduate school, which could be at any institution. Therefore, a violation of the exclusion restriction would require that undergraduates generalize from what they observe at their own institution and assume that all doctoral programs operate similarly.

Lastly, the minimum wage may directly influence the rate of pursuing higher education through a direct but unknown channel violating the exclusion restriction. To address this concern, we run a placebo test. We regress whether or not a student went on to earn a doctoral-level degree on minimum wage changes that occurred after the four years during which those students would have been in college. In Appendix F and Table A4 we show that this placebo test has insignificant coefficients on minimum wage changes occurring in the years after a student graduated. This placebo test provides supportive evidence that minimum wage changes do not directly influence the decision of these students to pursue doctoral-level studies.

While further information, including students' financial characteristics, would be required to conclusively rule out all potential exclusion violations, the available evidence is consistent with interpreting our instrumental variable estimates as reflecting the causal impact of exposure to scientific work on subsequent doctoral enrollment.

5 Conclusions

In this paper we have estimated the elasticity of academic scientists for lab personnel using rich administrative data from thousands of research labs facing price changes due to state minimum wage law changes.

We find that scientists employ fewer undergraduates and research staff in response to minimum wage changes, particularly those employing more undergraduates and research previously, and slightly increase their use of graduate students. We further investigated whether there were reallocation effects in which labs undergraduate research assistants were working in after minimum wage changes. Finally, we examined whether PIs changed the location of their subawards in response to minimum wage changes, but found no significant effects.

Our results demonstrate that even small changes in the cost of labor can have significant impacts on the employment of trainee researchers, such as undergraduate research assistants. This reduction in employment also means a reduction in the undergraduate students being exposed to scientific research, which may influence career choices in the future.

What would it cost to avoid the reduction in employment of undergraduate research assistants? We perform a rough estimate of this cost by considering how much labor costs would have increased for the undergraduate research assistants whose employment was reduced following the minimum wage changes. Specifically, we multiply the increase in the minimum wage by the estimated average reduction in undergraduate days of work. We assume that the average undergraduate research assistant works 4 hours per day of employment.³² Finally, we multiply this average number of hours by the number of labs in our dataset.

The results of this back-of-the-envelope calculation shows that for funding agencies to compensate all labs in our sample for the minimum wage increase for all of their undergraduate research assistants in 2019, the total cost would be on the order of \$4.96 million. For funding agencies to compensate the labs only for the share of undergraduate labor that typically declines following a minimum wage increase, the total would be approximately \$0.516 million per year. In 2019, the universities in our sample enrolled approximately 600,000 undergraduate students. The total number of undergraduate students enrolled in U.S. universities in that year was over 15 million. Assuming similar rates of students participating research across all universities in the country, the total cost to compensate the additional cost for all the undergrad research assistants may be on the order of \$133 million per year.

While these figures seems small relative to the total budgets of U.S. scientific funding agencies, our results demonstrate that even relatively small changes in the labor costs of labs can have sizable impacts. Given the uncertainty of changes in the cost of labor, our results point to the need for insurance mechanisms or increased budget flexibility by funders and university administrators. Universities seeking to provide undergraduates with research experience should consider providing faculty with alternate funding sources that are in line with minimum wage levels.

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³²We got this figure through a FOIA request of one large university in our sample.

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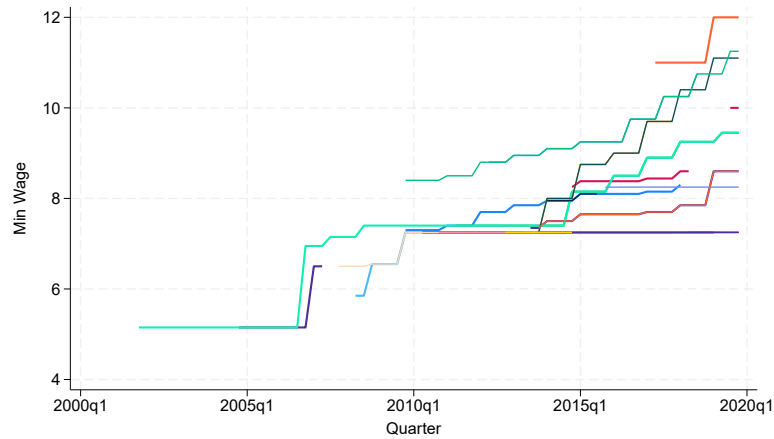
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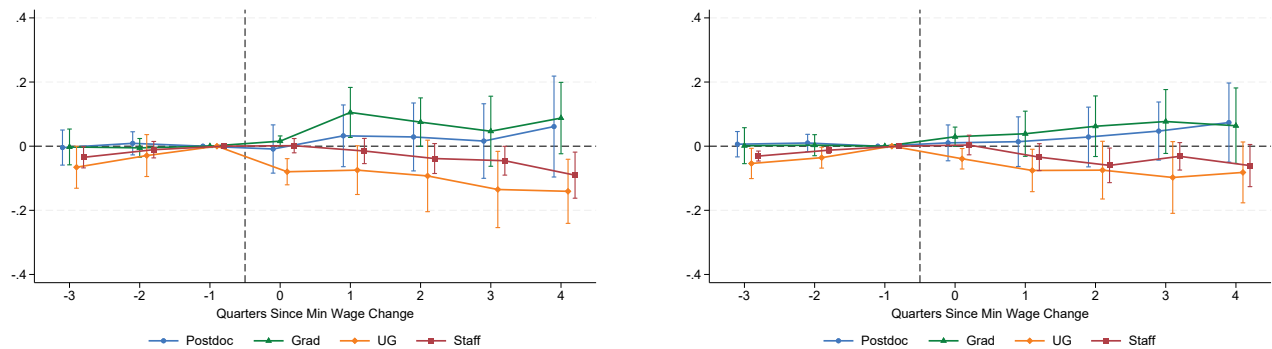
6 Figures and Tables

Figure 1. Minimum Wage Levels at Universities in Sample



Note: The above figure shows the minimum wage in each quarter at the universities in our sample. Each line in the graph represents one of the universities in the sample.

Figure 2. Main Effects Poisson Regressions

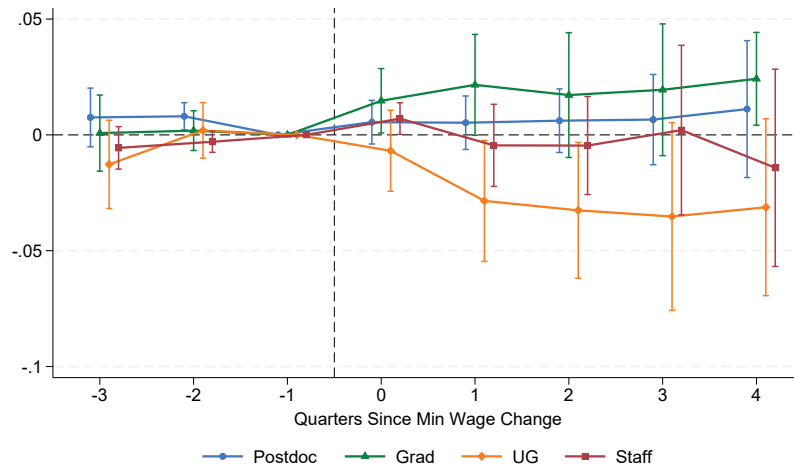


(A) Employee Days

(B) Distinct Employees

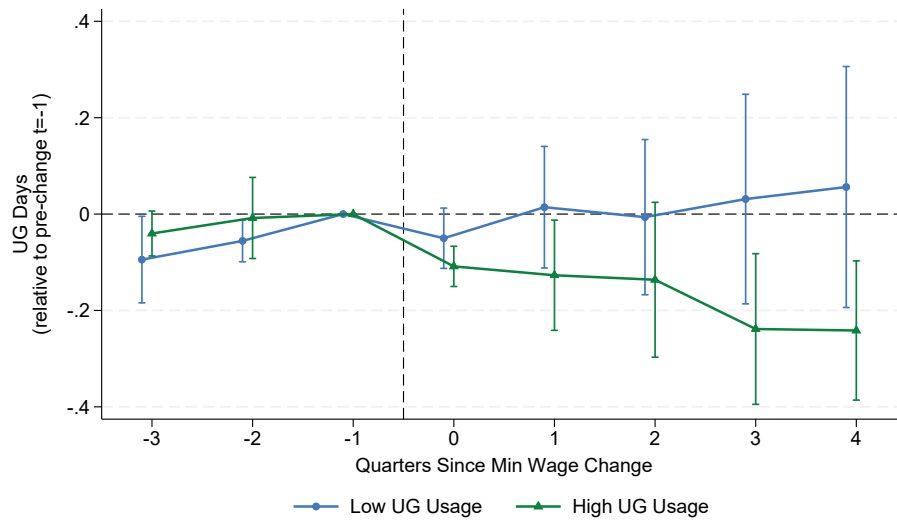
Note: The above figures plot the estimated coefficients from Equation 1 using a Poisson model and data from the Lab Panel. In Figure (a), the dependent variable is the number of days of employment. In Figure (b), the dependent variable is the number of distinct employees working in the lab in each quarter. Both of these figures plot the coefficients from estimating the equation separately by type of worker.

Figure 3. Probability of Employing Worker



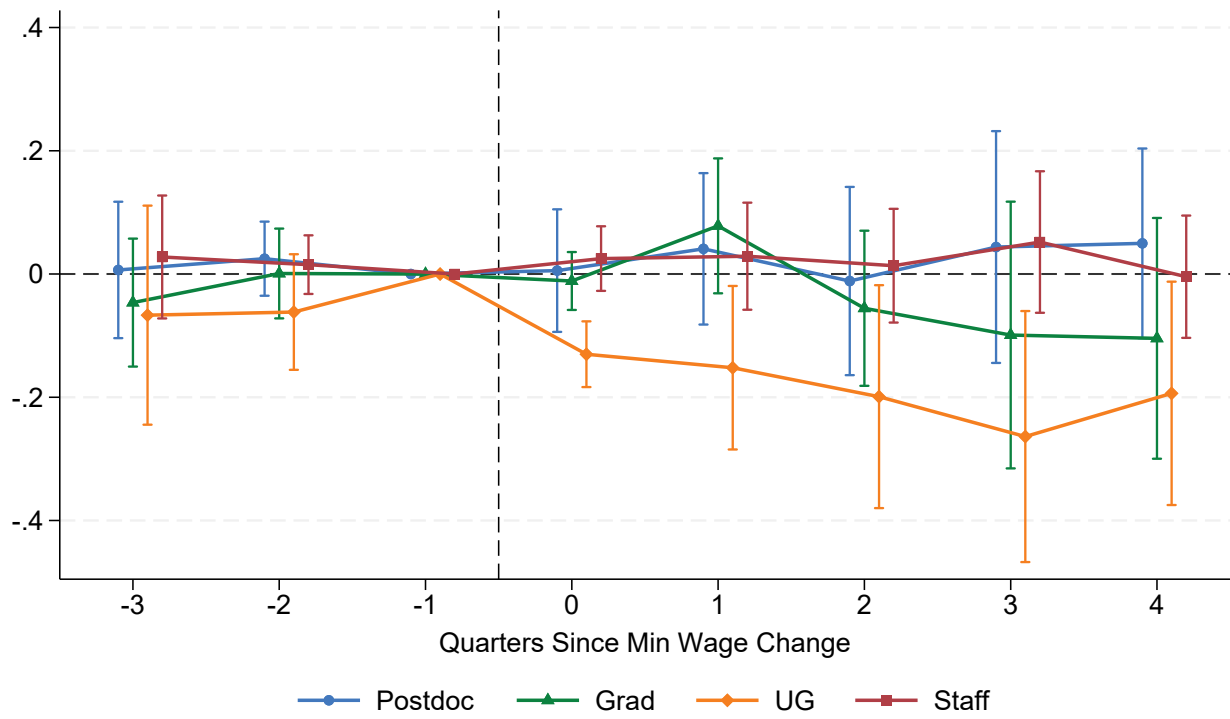
Note: The above figures plot the estimated coefficients from Equation 1 using OLS and data from the Lab Panel. The dependent variable is whether or not the lab employed at least one employee of each type of labor. The figure plots the coefficients from estimating the equation separately by type of worker.

Figure 4. Effect of Minimum Wage Changes by Intensity of Usage



Note: The above figures plot event study estimates and confident intervals from Equation 1. The dependent variable is the log number of days of work performed by undergraduates plus one. The regression model includes grant and quarter fixed effects. Standard errors are clustered at the university level. The blue line represents labs that had less than 10% of the days of work performed by employees in the lab be from undergraduates, while the green line shows those with more than 10%.

Figure 5. Event Study Estimates using Stacked Dataset



Note: The above figures plots the estimated coefficients from estimating an event study using the Stacked Dataset. The procedure is similar to the one used for Figure 2, except that in this one, we include event-specific lab and year fixed effects in the regression.

Table 1. Mean Attributes of Observations in Dataset

	Mean	P25	P50	P75
Panel A: Labs (N=11,377)				
PI Female	0.22	0.00	0.00	0.00
PI Age	47.87	39.75	47.11	55.37
Known PI	0.54	0.00	1.00	1.00
Panel B: Lab Panel Dataset (N=264,951)				
PI Female	0.21	0.00	0.00	0.00
PI Age	48.46	41.00	48.00	56.00
Known PI	0.61	0.00	1.00	1.00
Grants	2.47	1.00	2.00	3.00
Direct Expend	112,828.28	29,210.25	65,543.30	134,172.61
Vendor Spend	15,653.41	196.59	3,461.36	13,805.85
Postdocs	0.65	0.00	0.00	1.00
Grads	1.88	0.00	1.00	3.00
UGs	1.19	0.00	0.00	1.00
Staff	3.44	0.00	2.00	4.00
Panel C: Grant Panel Dataset (N=183,649)				
Direct Expend	50,255.58	13,765.41	30,150.32	58,226.80
Vendor Spend	6,866.11	0.00	900.10	5,045.84
Postdocs	0.32	0.00	0.00	0.00
Grads	1.03	0.00	1.00	1.00
UGs	1.01	0.00	0.00	1.00
Staff	1.69	0.00	1.00	2.00
Panel D: Production Dataset (N=72,684)				
WoS Publications	0.47	0.00	0.00	0.00
PubMed Publications	3.07	0.00	1.00	3.00
5 Year Citations	6.07	0.00	0.00	0.00
Panel E: UG Panel Dataset (N=192,529)				
Female	0.29	0.00	0.00	1.00
Age	21.05	19.00	20.00	22.00
Fed Work-Study	0.12	0.00	0.00	0.00
Employed in Lab	0.42	0.00	0.00	1.00
Panel F: Student Outcomes Dataset (N=28,283)				
Female	0.45	0.00	0.00	1.00
Qtrs Worked	1.44	0.00	0.00	2.00
Qtrs Worked NIH	0.69	0.00	0.00	0.00
Doctoral Degree	0.17	0.00	0.00	0.00
Industry: Life Sci.	0.03	0.00	0.00	0.00

Note: The above table provides summary statistics for the variables from across the various datasets used in our analysis.

Table 2. Effect of Minimum Wage Changes on the Employment of Undergraduates

	(1) Emp. Days Poisson	(2) Emps. Poisson	(3) Employ OLS	(4) Days/Emp OLS	(5) Intensive Poisson
ΔQ	-0.104** (0.041)	-0.074* (0.038)	-0.027** (0.013)	-0.015 (0.015)	-0.053 (0.038)
ϵ	-1.256** (0.490)	-0.886* (0.459)	-0.323** (0.157)	-0.188 (0.183)	-0.653 (0.473)
N	264951	264951	264951	113443	113443
N Labs	11377	11377	11377	10441	10441
Lab FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
R2	0.54	0.39	0.32	0.38	0.60
Dep. Mean	86.35	1.19	0.43	4.20	201.05

Standard errors in parentheses

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

Note: The above tables displays the ΔQ and ϵ estimates based on estimating Equation 1 using data from the Lab Panel. In Column (1), the dependent variable is the number of days of undergraduate employment in labs estimated using a Poisson model. In Column (2), the dependent variable is the number of distinct undergraduates employed in labs estimated using a Poisson model. In Column (3), the dependent variable is an indicator for the lab employing at least one undergraduate estimated using OLS. In Column (4), the dependent variable is the log-transformed number of days per employed undergraduate in labs that employed at least one undergraduate estimated using OLS. In Column (5), the dependent variable is the number of days of undergraduate employment in labs that employed at least one undergraduate estimated using a Poisson model.

Table 3. Heterogeneous Effects of Minimum Wage Changes on the Employment of Undergraduates

	Emp. Days UG								
	(1) UG Low	(2) UG High	(3) Bio.	(4) Phys. & Eng.	(5) Psy.	(6) NIH	(7) NSF	(8) <2	(9) >2
ΔQ	0.009 (0.080)	-0.170*** (0.059)	-0.126** (0.053)	-0.010 (0.047)	-0.092** (0.047)	-0.144*** (0.054)	-0.083 (0.056)	-0.117** (0.058)	-0.092** (0.037)
ϵ	0.105 (0.927)	-2.174*** (0.749)	-1.456** (0.610)	-0.126 (0.586)	-1.124** (0.573)	-1.662*** (0.627)	-1.079 (0.729)	-1.525** (0.760)	-1.024** (0.411)
N	120072	86289	151558	41672	157699	142024	71408	115705	126081
N Labs	5272	4095	6635	1451	7689	6367	3640	9132	7982
Lab FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.46	0.50	0.56	0.52	0.55	0.56	0.56	0.54	0.59
Dep. Mean	49.70	164.02	87.79	81.46	90.05	88.10	99.31	81.78	106.02

Standard errors in parentheses

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

Note: The above tables displays the ΔQ and ϵ estimates based on estimating Equation 1 with a dependent variable of the number of undergraduate days of employment using Poisson on sub-samples of data from the Lab Panel. Column (1) estimates this using labs that do not intensively employ undergrads. Column (2) estimates this using labs that do intensively employ undergrads. Column (3) estimates this using labs in the fields of biology and medicine. Column (4) estimates this using labs in the fields of physics and engineering. Column (5) and (6) estimates this using labs with funding from the NIH and NSF respectively. Column (7) and (8) estimates this using labs with grants that have less than 2 years remaining and more than 2 years remaining respectively.

Table 4. Effect of Minimum Wage Changes on Graduate Student Employment

	All		No Union		Unionized	
	(1)	(2)	(3)	(4)	(5)	(6)
	Emp. Days Grad Poisson	Emps. Grad Poisson	Emp. Days Grad Poisson	Emps. Grad Poisson	Emp. Days Grad Poisson	Emps. Grad Poisson
ΔQ	0.069** (0.033)	0.057 (0.040)	0.126* (0.076)	0.093 (0.062)	0.097** (0.040)	0.118*** (0.036)
ϵ	0.793** (0.377)	0.651 (0.459)	1.241* (0.749)	0.920 (0.615)	1.167** (0.478)	1.429*** (0.432)
N	228970	229039	91541	91569	137429	137470
N Labs	9538	9542	4686	4688	4852	4854
Lab FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.62	0.39	0.61	0.37	0.62	0.40
Dep. Mean	173.40	2.11	179.77	2.24	169.15	2.02

Standard errors in parentheses

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

Note: The above tables displays the ΔQ and ϵ estimates based on estimating Equation 1 using Poisson on sub-samples of data from the Lab Panel. Column (1) and Column (2) estimate with the dependent variable of the days of employment of grad students and the number of distinct grad students employed in labs across the full dataset. In Columns (3) and (4), we repeat these estimates on the sample of labs at universities without a graduate student union. In Columns (5) and (6), we repeat these estimates on the sample of labs at universities with graduate student unions.

Table 5. Employment Effects With Grant Life-cycle Controls and Institution Time Trends

	Last Qtr FE			Inst. Seasonality			Inst. Trend		
	(1) Emp. Days Poisson	(2) Emps. Poisson	(3) Employ OLS	(4) Emp. Days Poisson	(5) Emps. Poisson	(6) Employ OLS	(7) Emp. Days Poisson	(8) Emps. Poisson	(9) Employ OLS
ΔQ	-0.105** (0.041)	-0.074* (0.038)	-0.027** (0.013)	-0.086** (0.037)	-0.062 (0.038)	-0.027* (0.014)	-0.093** (0.047)	-0.068* (0.039)	-0.032** (0.013)
ϵ	-1.263** (0.490)	-0.890* (0.461)	-0.324** (0.158)	-1.036** (0.440)	-0.744 (0.462)	-0.320* (0.164)	-1.117** (0.566)	-0.818* (0.475)	-0.380** (0.161)
N	264951	264951	264951	264951	264951	264951	264951	264951	264951
N Labs	11377	11377	11377	11377	11377	11377	11377	11377	11377
Lab FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inst. Qtr. FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Inst. Trends	No	No	No	No	No	No	Yes	Yes	Yes
R2	0.54	0.39	0.32	0.54	0.39	0.33	0.54	0.39	0.33
Dep. Mean	86.35	1.19	0.43	86.35	1.19	0.43	86.35	1.19	0.43

Standard errors in parentheses

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

Note: The above tables displays the ΔQ and ϵ estimates based on estimating Equation 1 using data from the Lab Panel. In Column (1), the dependent variable is the number of days of undergraduate employment in labs estimated using a Poisson model. In Column (2), the dependent variable is the number of distinct undergraduates employed in labs estimated using a Poisson model. In Column (3), the dependent variable is an indicator for the lab employing at least one undergraduate estimated using OLS. In all columns, we include a fixed effect for if the lab had a grant which stopped being charged in that quarter. In addition, in columns (4)-(6), we include institution-by-quarter of the year fixed effects, and, in columns (7)-(9), we include institution specific time trends.

Table 6. Effect of Minimum Wage Changes on Undergraduate Employment Using Stacked Dataset

	(1) Emp. Days Poisson	(2) Emps. Poisson	(3) Employ OLS	(4) Days/Emp OLS	(5) Intensive Poisson
ΔQ	-0.242*** (0.050)	-0.192*** (0.039)	-0.044** (0.021)	-0.051** (0.025)	-0.143*** (0.035)
ϵ	-2.669*** (0.555)	-2.125*** (0.433)	-0.486** (0.229)	-0.555** (0.279)	-1.559*** (0.382)
N	6392919	6392919	6392919	2782282	2782282
N Labs	11377	11377	11377	11373	11373
Event-Lab FE	Yes	Yes	Yes	Yes	Yes
Event-Quarter FE	Yes	Yes	Yes	Yes	Yes
R2	0.55	0.40	0.35	0.38	0.62
Dep. Mean	82.18	1.16	0.44	4.16	188.83

Standard errors in parentheses

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

Note: The above table displays the estimated coefficients from estimating the Stacked Dataset. The columns and variables are similar to Table 2. In the above regressions, however, we include event-specific lab and quarter fixed effects.

Table 7. Grant-Level Analysis

	All			NIH Grants		
	(1) Emp. Days Poisson	(2) Emps. Poisson	(3) Employ OLS	(4) Emp. Days Poisson	(5) Emps. Poisson	(6) Employ OLS
ΔQ	-0.092*** (0.022)	-0.059** (0.028)	-0.022** (0.010)	-0.103*** (0.037)	-0.079* (0.042)	-0.040*** (0.013)
ϵ	-1.168*** (0.283)	-0.751** (0.349)	-0.284** (0.127)	-1.239*** (0.444)	-0.950* (0.513)	-0.480*** (0.160)
N	183649	183649	183649	72006	72006	72006
N Labs	17845	17845	17845	7461	7461	7461
Grant FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.56	0.37	0.35	0.58	0.38	0.37
Dep. Mean	70.94	1.01	0.48	76.51	1.05	0.51

Standard errors in parentheses

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

Note: The above tables displays the ΔQ and ϵ estimates based on estimating Equation 1 using data from the Grant-by-Quarter Panel. In Column (1), the dependent variable is the number of days of undergraduate employment charged to a grant estimated using a Poisson model. In Column (2), the dependent variable is the number of distinct undergraduates charged to a grant estimated using a Poisson model. In Column (3), the dependent variable is an indicator for a grant employing at least one undergraduate estimated using OLS.

Table 8. Effect of Minimum Wage Changes on Scientific Paper Production

	(1) WoS Pubs. Poisson	(2) Pubmed Pubs. Poisson	(3) 5 Year Cites. Poisson
ΔQ	0.010 (0.035)	0.030 (0.063)	0.100 (0.086)
ϵ	0.128 (0.465)	0.382 (0.814)	1.281 (1.102)
N	28800	50498	24006
N Labs	3663	6862	3298
Lab FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
R2	0.75	0.64	0.79
Dep. Mean	1.18	4.42	18.39

Standard errors in parentheses

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

Note: The above tables displays the estimated coefficients from estimating Equation 5 using a Poisson model and data from the lab-by-year Panel. In Column (1), the dependent variable is the number of publications linked to grants from the lab published in the year and linked to Web of Science. In Column (2), the dependent variable is the number of publications linked to grants from the lab published in the year and linked to PubMed. In Column (3), the dependent variable is the number of publications linked to grants from the lab published in the year and linked to Web of Science and weighted by the number of citations to those publications in the five years after publication.

Table 9. Aggregate Effects of Minimum Wage Changes

	All						NIH Funded
	(1) Grants Poisson	(2) Spending OLS	(3) Labor OLS	(4) Supplement OLS	(5) Subaward Poisson	(6) Min Wage (wt) Poisson	(7) Supplement OLS
ΔQ	-0.004 (0.012)	-0.012 (0.023)	0.016 (0.021)	0.002*** (0.000)	-0.094 (0.133)	-0.003 (0.059)	0.005*** (0.001)
ϵ	-0.046 (0.145)	-0.143 (0.275)	0.195 (0.249)	0.018*** (0.006)	-1.134 (1.604)	-0.037 (0.713)	0.053*** (0.013)
N	264951	264951	261621	264951	143139	139475	143976
N Labs	11377	11377	11369	11377	5457	5303	6552
Lab FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.21	0.50	0.48	0.48	0.59	0.31	0.47
Dep. Mean	2.47	10.97	10.74	0.02	27,041.69	3.75	0.02

Standard errors in parentheses

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

Note: The above tables displays the ΔQ and ϵ estimates based on estimating Equation 1 using data from the Lab Panel. Column (1) uses a dependent variable of the number grants being charged by a lab in a quarter and Poisson. Column (2) uses a dependent variable of an indicator for the lab charging a new grant starting in that quarter and OLS. Column (3) uses a dependent variable of the log transformed direct expenditures of a lab and OLS. Column (4) uses a dependent variable of an indicator for the lab charging a supplement starting in that quarter and OLS. Column (5) uses a dependent variable of the total amount of subaward dollars associated with a lab in a quarter and Poisson. Column (6) uses a dependent variable of the total amount of subaward dollars associated with a lab in a quarter weighted by the minimum wage in the state where the subaward is being sent and Poisson. Column (7) uses a dependent variable of an indicator for the lab charging a supplement starting in that quarter and OLS using the subset of labs funded by NIH.

Table 10. Effect of Minimum Wage Changes on Undergraduates Working in Labs

	UG Panel					
	(1) Employed OLS	(2) Employed OLS	(3) Employed OLS	(4) Employed OLS	(5) PubMed Pubs OLS	(6) Lab Size OLS
Min Wage Change	-0.056*** (0.014)	-0.152*** (0.011)	-0.044** (0.015)	-0.066*** (0.012)	0.002 (0.045)	0.128* (0.063)
Experience		-0.089*** (0.019)	-0.082*** (0.017)	-0.082*** (0.017)		
Min Wage Change x Experience		0.038*** (0.005)				
Min Wage Change x Female			-0.014 (0.013)			
Min Wage Change x FWS				0.042* (0.022)		
N	191946	191946	191946	191946	61163	75697
N UGs	26497	26497	26497	26497	15951	20118
UG FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.60	0.62	0.61	0.61	0.91	0.93
Dep. Mean	0.42	0.42	0.42	0.42	0.21	1.89
F-stat	14.81	67.00	12.21	91.60	0.00	4.15

Standard errors in parentheses

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

Note: The above table shows the estimates from OLS regressions on an indicator for the minimum wage changing using observations from the Undergraduate x Quarter Panel. Across all the columns, the dependent variable is an indicator for the undergrad being employed in a lab. Experience is measured as the number of quarters in which the undergrad was previously employed. FWS is an indicator for the undergrad having ever been paid on a Federal Work-Study account in our dataset.

Table 11. Effect of Minimum Wage Changes on Undergraduates Career Outcomes

	End.	FS		RF		IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Ph.D.	Qrts.	Qrts.	Ph.D.	Ph.D.	Ph.D.	Ph.D.
Qtrs Worked	0.010*** (0.002)					0.070*** (0.024)	0.103*** (0.016)
MWage		-0.260*** (0.051)		-0.018** (0.008)			
MWage Yr1			-0.233*** (0.042)		-0.032*** (0.007)		
MWage Yr2			-0.288*** (0.053)		-0.024*** (0.004)		
MWage Yr3			-0.035 (0.086)		-0.001 (0.003)		
MWage Yr4			0.010 (0.062)		0.003 (0.003)		
Constant	0.155*** (0.003)	1.553*** (0.023)	1.565*** (0.015)	0.178*** (0.003)	0.183*** (0.002)	0.290*** (0.040)	0.233*** (0.029)
N	28,283	28,283	28,283	28,283	28,283	28,283	28,283
Inst FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grad Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.08	0.05	0.05	0.08	0.08	.	.
Dep. Mean	0.17	1.44	1.44	0.17	0.17	0.17	0.17
F	21.36	25.88	59.34	5.75	39.95	.	.

Standard errors in parentheses

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

Note: The above table shows the instrumental variable estimates for the effect of being employed in a university research lab on pursuing a doctoral degree. Column (1) shows the endogenous regression where the dependent variable is pursuing a doctoral-level degree. Columns (2) and (3) show the coefficients from estimating Equation 2 using either one instrument, the minimum wage changing during a student's college years, or four instruments, one indicator for minimum wage changes in each of the four years of college. Columns (4) and (5) show the estimates of the reduced form regression. Finally, the last two columns provide the 2SLS estimates of Equation 3. All columns include institution and graduation year fixed effects. Standard errors are clustered at the institution level.

Table 12. Effect of Minimum Wage Changes on Undergraduates Career Outcomes

	End.	FS		RF		IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	L.Sci.	Qrts.	Qrts.	L.Sci.	L.Sci.	L.Sci.	L.Sci.
Qtrs Worked	0.003 (0.002)					0.024*** (0.008)	0.018*** (0.004)
MWage		-0.260*** (0.051)		-0.006*** (0.002)			
MWage Yr1			-0.233*** (0.042)		-0.007** (0.003)		
MWage Yr2			-0.288*** (0.053)		-0.003* (0.001)		
MWage Yr3			-0.035 (0.086)		-0.001 (0.002)		
MWage Yr4			0.010 (0.062)		-0.000 (0.003)		
Constant	0.028*** (0.003)	1.553*** (0.023)	1.565*** (0.015)	0.035*** (0.001)	0.035*** (0.001)	0.008 (0.014)	0.019*** (0.006)
N	28,283	28,283	28,283	28,283	28,283	28,283	28,283
Inst FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grad Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.02	0.05	0.05	0.02	0.02	.	.
Dep. Mean	0.03	1.44	1.44	0.03	0.03	0.03	0.03
F	2.15	25.88	59.34	14.69	9.67	.	.

Standard errors in parentheses

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

Note: The above table shows the instrumental variable estimates for the effect of being employed in a university research lab on working in the life sciences industry. Column (1) shows the endogenous regression where the dependent variable is pursuing a doctoral-level degree. Columns (2) and (3) show the coefficients from estimating Equation 2 using either one instrument, the minimum wage changing during a student's college years, or four instruments, one indicator for minimum wage changes in each of the four years of college. Columns (4) and (5) show the estimates of the reduced form regression. Finally, the last two columns provide the 2SLS estimates of Equation 3. All columns include institution and graduation year fixed effects. Standard errors are clustered at the institution level.

Table 13. Effect of Minimum Wage Changes on Undergraduates Career Outcomes

	End.	FS		RF		IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	L.Sci.	Qrts.	Qrts.	L.Sci.	L.Sci.	L.Sci.	L.Sci.
Qtrs NIH	0.004 (0.003)					0.022*** (0.007)	0.020*** (0.005)
MWage		-0.282*** (0.052)		-0.006*** (0.002)			
MWage Yr1			-0.192*** (0.028)		-0.007** (0.003)		
MWage Yr2			-0.210*** (0.020)		-0.003* (0.001)		
MWage Yr3			-0.103 (0.061)		-0.001 (0.002)		
MWage Yr4			-0.022 (0.034)		-0.000 (0.003)		
Constant	0.029*** (0.002)	0.813*** (0.023)	0.808*** (0.010)	0.035*** (0.001)	0.035*** (0.001)	0.023*** (0.008)	0.025*** (0.005)
N	28,283	28,283	28,283	28,283	28,283	28,283	28,283
Inst FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grad Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.02	0.02	0.03	0.02	0.02	.	.
Dep. Mean	0.03	0.69	0.69	0.03	0.03	0.03	0.03
F	2.07	29.54	161.58	14.69	9.67	.	.

Standard errors in parentheses

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

Note: The above table shows the instrumental variable estimates for the effect of being employed in a university research lab on working in the life sciences industry. The main endogenous variable of interest is the number of quarters that a student worked in a lab funded by the NIH. Column (1) shows the endogenous regression where the dependent variable is pursuing a doctoral-level degree. Columns (2) and (3) show the coefficients from estimating Equation 2 using either one instrument, the minimum wage changing during a student's college years, or four instruments, one indicator for minimum wage changes in each of the four years of college. Columns (4) and (5) show the estimates of the reduced form regression. Finally, the last two columns provide the 2SLS estimates of Equation 3. All columns include institution and graduation year fixed effects. Standard errors are clustered at the institution level.

Supplemental Appendix

Ina Ganguli Raviv Murciano-Goroff

A Data and Samples

A.1 UMETRICS Data

The main source of raw data is the UMETRICS database curated by The Institute for Research on Innovation & Science (IRIS). We utilize the 2020 release of this database.

This database provides transaction-level charge information to accounts at participating universities. The accounts covered by UMETRICS varies somewhat across the universities, with some providing information all research accounts and others only providing information on sponsored research accounts.

The main transactions in the UMETRICS database are associated either with vendor spending or employment. All transactions provide the grant number or account number for which the transaction was charged. The transactions on vendor spending include the name of the merchant and total amount spent. The transactions on employment include an anonymized employee ID, the start and end of the period of employment, and the job title of the employee. In addition, IRIS, based both on job titles and information provided by the universities, also provides an occupational classification code for each employee. These codes include “Faculty,” “Post Doctoral Researcher,” “Graduate Student,” and “Undergraduate,” and “Research Staff.” For each employee, UMETRICS also provides a gender based on imputation from the names as well as data provided by the universities directly.

Note that we do not observe salaries or compensation. For privacy reasons, the UMETRICS data does not provide that information. In addition, the UMETRICS data does not provide any information about students educational record. In particular, we do not directly observe students’ year of graduation, exact age, or grades.

Each university provided data to UMETRICS during different periods of time. The coverage for each university can be found in the document of the UMETRICS data. We focus only on the universities that provided complete data on employment and the direct expenditures of their accounts. We drop any universities that provide data on only some employees types, such as those that do not provide information about undergraduate employees, or that have incomplete data for some quarters, such as those with fewer than 10 undergrads and grad students listed as employees in the sample of labs used in our analysis. We also drop universities that provide both direct expense transaction data and employee data but not provide a means to link these to the same grant or account. Lastly, we drop the first and last quarter of data for all labs from a university as charges are frequently not immediately posted to accounts and these quarters often have incomplete data .

In all of our work with UMETRICS, we exclude grants with nondescript grant or account numbers. For example, we drop any grants with grant numbers such as “000” or “Not Applicable” or “Agreement”. In general, these are administrative accounts that cannot be associated with a particular individual.

In addition, we remove any grants sponsored by the Department of Education. Many of these grants are graduate fellowships or other student funding that cannot be associated with a particular

lab. This is because, for example, if a graduate student works in a lab but is entirely paid on a fellowship from the Department of Education then there is no payment to the PI and we would not be able to attach that fellowship back to the lab that the student worked in.

We also exclude grants specifically intended for research centers rather than for specific labs or research projects. For example, we exclude NIH grants with activity codes such as G12, M01, P01, P20, P2C, P30, P40, P42, P50, P51, P60, PL1, PM1, PN1, PN2, T42, U48, U54, UL1, and ULTR. We also exclude grants for which more than 12 faculty are paid (the 99th percentile of the number of faculty paid per grant) as these grants tend to be funding research centers or departments. After applying all of these filters, our lab-by-quarter panel contains information on 11,377 labs across 23 universities.

A.2 Minimum Wage Data

Data on the minimum wage comes from [Zipperer and Vaghul \(2016\)](#). The authors provide data updated through 2022 on GitHub.³³ We utilize the quarterly state-level minimum wage data release. For all of our analysis, we focus on the nominal state minimum wage. While universities frequently have multiple campuses, we apply attach these minimum wage data to UMETRICS data based on the state of the main campus of the universities in our sample.

A.3 Steppingblocks Data

Steppingblocks is a company that collects information on student outcomes for use by universities. IRIS has created a linkage between the Steppingblocks data and the UMETRICS employee records. IRIS performs this matching using personally identifiable information that is not available to us.

The linkage provided to us shows the educational degrees achieved by employees who appear in the UMETRICS data classified as an undergraduate, as well as the year of their degree.

In addition, Steppingblock provides information on the industries in one an individual has worked in their employment data. While this is more sparsely populated, we f

A.4 Lab Panel Dataset Sample

Imputing laboratories from the UMETRICS data is one of the first steps in the construction of the datasets used for our main analysis. Our process for identifying labs is as follows:

First, we identify all of the employees in the UMETRICS employment records where the employee was paid on a grant and listed under the occupation “Faculty.” Among those, we filter to individuals who are only paid under the occupation during any employment.³⁴ We also filter to individuals who worked at least three years in the UMETRICS employment data. We call these Principal Investigators (PIs).

Second, we identify all of the grants associated with a PI. We do this by collecting any grants that paid the PI at any time in the UMETRICS employment data. We exclude any grants intended for research centers rather than individuals projects, both by excluding NIH grants categorized as center grants as well as any grants that paid more than 12 distinct faculty members. We also excluded grants with titles indicating that they were for “Clinical Services” or “Scholarships”. We also only include

³³<https://github.com/benzipperer/historicalminwage/releases>

³⁴We exclude individuals who, for example, are paid as both “Faculty” and “Staff” or “Faculty” and “Postdoc”.

grants that paid employees, made purchases at a vendor, and had non-negative total expenses.³⁵

We call this set of grants associated with a PI a “lab.” For our analysis, we focus on the time period before 2020 as the COVID-19 pandemic created a variety of disruptions that would make it hard to isolate the effects of minimum wage changes. Finally, in order to have the same number of observations in our regressions, we restrict to only labs that have variation in the number of undergraduate days of employment across their observations. We do this because labs without such variation would be dropped from our two-way fixed effects regressions as singletons.

For each lab, we create a balanced set of observations between the first quarter that the lab either employed or had direct expenses and the last quarter. Any quarters with no employment or expense data are imputed with zeros.

A.5 Undergraduate Panel Dataset Sample

For this dataset, we wish to track undergraduates during their time in college to see if they work in a research lab. The constraint is that we do not directly observe when individuals in the UMETRICS data begin and end their college education, nor do we observe their exact age for privacy reasons.

The construction of this dataset is as follows:

First, we find any individual listed in the UMETRICS employment data as working in a research lab in our Lab Panel Dataset sample and listed as an undergraduate.

Second, for each of these individuals, we create 8 quarterly observations starting from the first quarter in which we observe the individual working in a UMETRICS lab. Our goal here is to create a balanced set of observations during a time when we believe that it is highly likely that the student is still an undergrad and has not yet graduated.

Third, with each individual and their quarterly observations, we attach whether or not that student worked in a research lab from our sample in that quarter.

Fourth, we flag if an individual can be associated with Federal Work Study. Not all universities provide data on non-sponsored grant accounts, so our coverage of these accounts is limited. Our approach is to scan the employment data for any accounts with the keywords of “Work Study” or “FWS” in the title of the account. We also flag if a student is female. IRIS provides this information based on imputations of the name and cross-validated with actual genders provided by a subset of the UMETRICS institutions. More information about that procedure and validations of the approach can be found in [Ross et al. \(2022\)](#).

Lastly, we attach the minimum wage levels and whether or not the minimum wage changed in each quarter.

In order to match our Lab Panel Dataset, we again drop any undergrads at universities without complete data or where employment and vendor or direct expense data cannot be linked. We also filter to only quarters prior to 2020 to avoid the disruptions caused by the COVID-19 pandemic and drop any time period outside of the range of UMETRICS coverage for the university that the individual is associated with. Finally, we only analyze individuals where we observe the individual for the full 8

³⁵Negative expenses could occur for a variety of reasons. Some universities allow labs to spend funds prior to receiving promised funds from a funding agency. In addition, when vendor expenses are reversed or refunded the negative charges can be created in the data.

quarters after applying these filters.

A.6 Student Outcomes Dataset Sample

For this dataset, we utilize the intersection of the UMETRICS data and the Steppingblocks data. Our goal is to examine how time spent working in a research lab impacts whether or not undergrad research assistants go on to doctoral degrees and other career outcomes. The constraint on this exercise is that we only observe undergrads who worked at their university at some point.

Our data construction procedure is as follows:

First, we find all individuals who appeared in the UMETRICS employment data, were listed as an undergraduate, and can be linked by IRIS to a record in Steppingblocks.

Second, we filter to those whose records in Steppingblocks provides a graduation year from college. For this group, we create a panel of quarterly observations between September four years prior to their graduation year and June of their graduation year.

Third, we note which of those months the individual is observed working in a research lab in our data. We count the distinct months worked (e.g. if an individual worked in multiple labs or had multiple employment records for the same month in the same lab then we count those as one month of work). We separately count the number of months worked in labs sponsored by NIH, other federal funds, or non-federal funds. Note that only some universities provide complete coverage of transactions to non-sponsored research accounts.

Fourth, for each individual, we note if their data in Steppingblocks lists a doctoral level educational degree. We also separately flag if an individual went on to a J.D. or M.D. We also note if the employment records listed among the individual's Steppingblocks data are categorized as in the industries of life science, legal, financial, or healthcare. Note that for privacy reasons, IRIS and Steppingblocks do not provide us with access to their raw data sources or individuals' job titles, employer names, university names, etc.

Fifth, we combine this data and aggregate to the individual level. For all the individuals in our sample, we attach the total number of quarters worked. We also attach their career outcomes. Finally, we attach whether or not the minimum wage changed during each year during their undergraduate time.

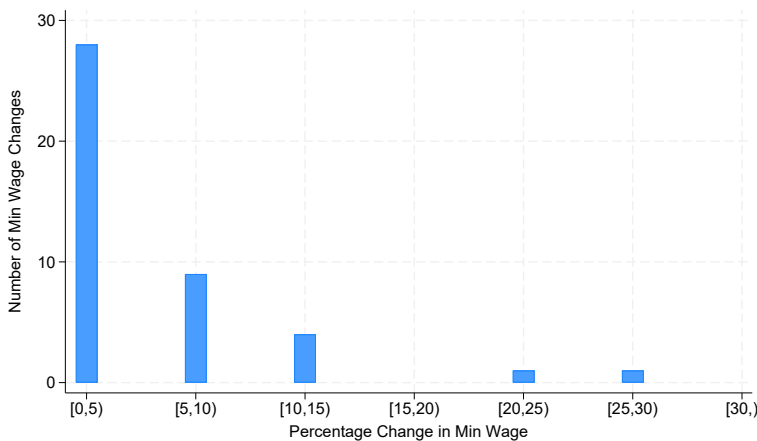
In order to make this analysis consistent with the Lab Panel Dataset, we also filter out of this dataset any individuals whose undergraduate time was at a university where we do not have complete data or cannot match employment records with vendor and direct expense data.

We also require that any individual analyzed in this dataset worked at least one month in the UMETRICS data during the time between September four years prior to their college graduation and June of their college graduation year. We impose this restriction for two reasons. First, we want to focus on students who worked as research assistants during their college years as opposed to individuals who worked in postbaccalaureate positions after they graduated. Our conjecture is that individuals who work as post-baccs are likely to have different work experiences. For example, post-baccs may have worked full-time, while undergraduate research assistants are likely to have worked part-time. Second, UMETRICS occupation classifications are imperfect and some individuals whose employment record is listed as "undergraduate" may have actually been "staff" or even a "graduate student". For example, an employment record with the job title "Lab Assistant" may have been an un-

dergrad research assistant or a staff position. If we inaccurately treated an individual as an undergrad when in fact they were already a graduate student or staff with advanced degree, we would measure no time working as an undergraduate in the UMETRICS data, since any work in a lab would occur after their year of college graduation, but we would flag them as going on to a doctoral degree. As Steppingblocks provides the years of college graduation, for the sub-set of individuals in UMETRICS who can be linked to Steppingblocks, we believe that this enables identifying the years that an individual was an undergrad with high-fidelity. By only looking at individuals who we observe working as an undergraduate during the years for which the Steppingblocks data says that the individual was an undergrad, we believe that we accurately identify the individuals of interest for the exercise we analyzed.

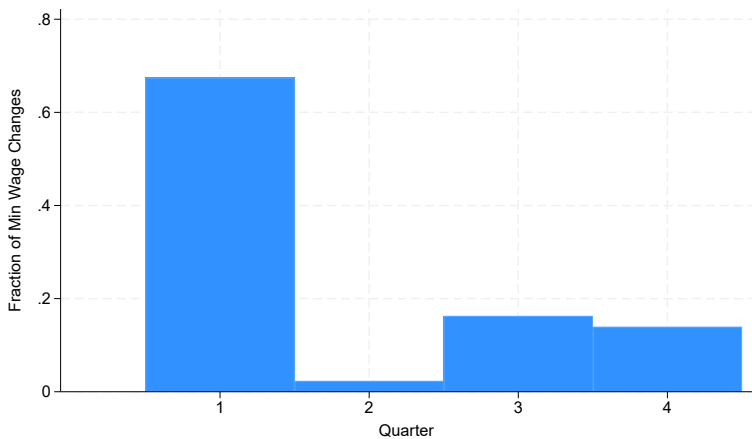
B Descriptives about Minimum Wage Changes

Figure A1. Distribution of the Magnitude of Minimum Wage Changes



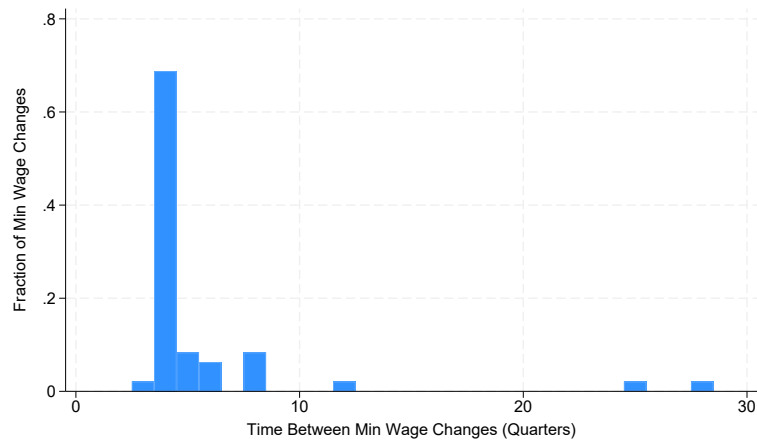
Note: The above histogram shows the distribution of minimum wage change in our sample based on the size of the minimum wage increase.

Figure A2. Distribution of the Quarter of Minimum Wage Changes



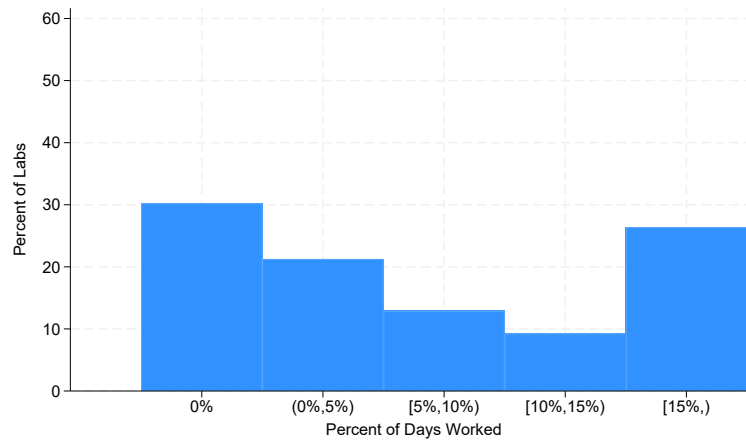
Note: The above histogram shows the distribution of minimum wage changes in our sample based on the quarter in which the minimum wage increased.

Figure A3. Distribution of Time Between Minimum Wage Changes



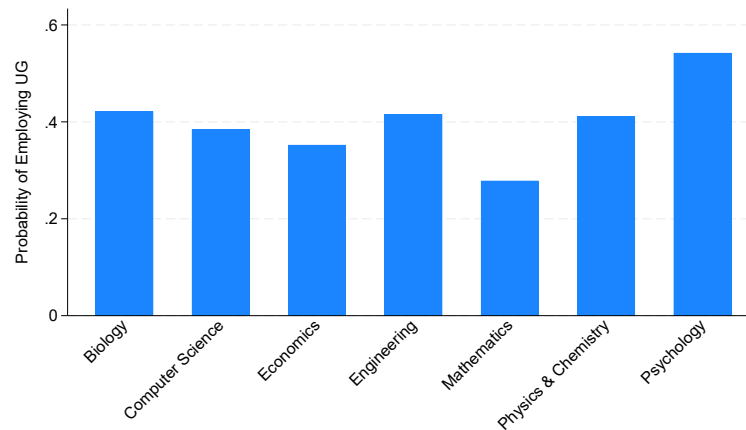
Note: The above histogram shows the distribution of minimum wage changes in our sample based on the number of quarters between changes.

Figure A4. Distribution of Fraction of Work Done in Labs by Undergraduates



Note: The above histogram shows the distribution of labs in our sample based on the share of work we observe that is undertaken by undergrads.

Figure A5. Probability of Employing an Undergrad by Field

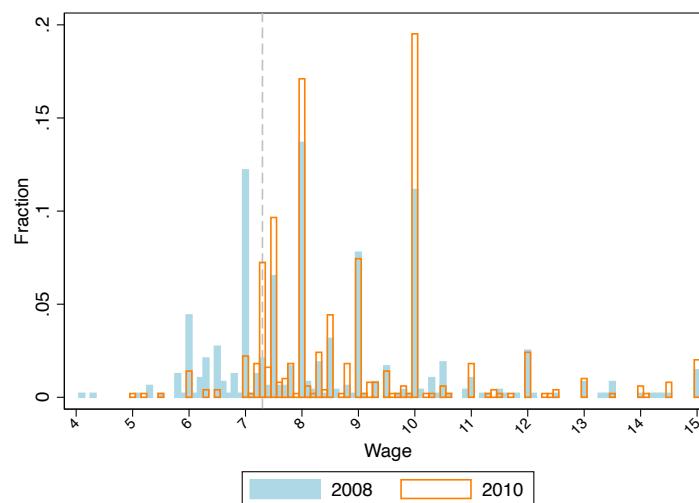


Note: The above plot shows the probability that a lab employs an undergrad based on the field of the lab. Note that only a subset of the labs in our sample have listed fields.

C CPS Data and Minimum Wage Changes

As the UMETRICS data does not provide individual wages or salary, we demonstrate that the minimum wage impacts the wages of individuals working at universities. In Figure A6, we show the distribution of hourly wages for workers at universities in 2008 and 2010. Note that the CPS does not specifically provide data on student employees. In 2009, the federal minimum wage increased. The figure shows that the portion of the wage distribution below the new minimum wage disappears and is shifted upward. This implies that the minimum wage does impact workers at universities.

Figure A6. Minimum Wages and University Employment, CPS



Note: The above figure shows the hourly wage distribution for university employees in 2008 and 2010 in the Current Population Survey – before and after the increase in the federal minimum wage in 2009 to 7.25.

D First-stage Evidence of the Minimum Wage Impacting Lab Costs

UMETRICS does not provide the actual wages of individual employees, and therefore we cannot directly show that increases in the minimum wage increase the wages of undergrad workers or what share of undergrad workers are paid the minimum wage versus a higher or lower wage. In this section, however, we show that the average wage of undergraduate workers at the universities in our sample is close to the actual minimum wage faced by labs. We also estimate the share of workers earning hourly wages less than or equal to the minimum wage based on the empirical CDF of our imputed wages. Finally, we provide evidence that changes in the minimum wage are associated with commensurate increases in labor costs for labs that continue employing the same number of workers.

For this analysis, we leverage a subset of the UMETRICS data that allows us to focus on the costs associated with undergraduate employees. We start with all the grant-by-month observations in UMETRICS. We impute the total labor costs charged to the grant in that month by subtracting the vendor and subaward payments from the direct expenses. Note that this is an imperfect measure of the actual labor cost. Many universities exclude internal charges, such as payments to departments within a university, from the UMETRICS dataset despite these being included in the total direct expense amount. Therefore, our imputed measure of labor costs is likely noisy and potentially an upper bound on the true labor cost.

For a subset of the universities in UMETRICS, we can compute the number of hours of work performed by undergrads and charged to each grant in each month. While all universities in UMETRICS provide the start and end date of employment for each employee, allowing us to measure the days of work billed to a grant, a smaller number of universities also provide the “full-time status” of the employee (measured as a percentage). For the subsample of grants at the universities providing that additional field, we use that data to construct the number of hours work performed by undergrad workers by multiplying the days of work by 8 hours and multiplying that by the full-time status percentage. We then sum that amount across all of the workers employed by a grant in a month. While somewhat imprecise, this provides a rough estimate for the number of hours worked by these employees.

We filter to the grant-by-month observations that give us the best visibility into the undergraduate labor costs. Specifically, we filter to grant-by-month observations from our analytical sample that only paid undergraduate employees, and no other types of employees, had positive direct expenses (i.e. charges to the grant), positive labor costs (i.e. direct expenses exceeded subaward and vendor expenses), and had positive undergrad hours charged. We only use observations from the universities that populate the FTE status variable.³⁶ Finally, we exclude observations from June, July, and August, as summer research assistants are less likely to have accurate FTE statuses listed. In total, we have 9,115 grant-by-month observations in this sample.

Using this data and imputed measures of labor costs and hours worked, we estimate the average wage earned by undergraduate workers and show that this wage is close to the minimum wage. The total labor cost of a grant in our sample in a month should be equal to the number of hours of

³⁶We ascertain that by looking for universities with positive variation in their FTE status variable. Other universities often do not populate that variable or list all employees with an FTE status of 1.

work performed by undergraduates that month times the wage of those employees.³⁷ Therefore, our empirical approach is a hedonic regression in which we regress the labor costs of grants on the number of hours of work billed for undergraduate workers. An advantage to estimating this via regression is that we can include fixed effects for the grant, which can absorb time-invariant internal charges from a grant to a university, which might be inflating the labor cost measure, and thus, the estimated hourly wage. Table A1 shows the results of this estimation. Column (1) shows the coefficient on the hours of work is 11.595, which implies that across the grants, one hour of additional work from an undergrad would be paid approximately \$11.60 per hour. Column (2) shows the same estimated coefficient after controlling for both grant fixed effects and quarter fixed effects. The estimated coefficient, 7.31. The average minimum wage across the grant-by-month observations in this subsample is \$7.51. Therefore, our estimate of the average per hour wage for undergraduate employees is close to the true average minimum wage.³⁸

Table A1. Hedonic Regression

	Labor Pay	
	(1)	(2)
Hours	11.595 (7.343)	7.310 (5.222)
Constant	1772.088*** (572.331)	1,976.347*** (493.813)
N	9,115	8,058
Grant FE	No	Yes
Month FE	No	Yes
R2	0.02	0.49
Dep. Mean	2,875.82	2,667.58

Note that in theory, one could estimate the coefficient for each university and compare the estimated coefficient with the actual minimum wage for that university. In reality, however, the number of grants that only employ undergraduates is small, with many universities have fewer than 30 such grants. Therefore, we do not attempt that exercise.

Instead, we use the empirical CDF of the undergrad hourly wage (labor cost / hours) to estimate the share of undergrads making at or below the minimum wage for their institution. For each grant-month, we flag if the implied hourly wage for undergrads in that lab was at or below the minimum wage, since students in these labs would be most impacted by increases in the minimum wage. We then weight by the number of undergrads working on those grants to find the share of undergrad RAs making at or below the minimum wage in this sample. Based on the full sample, 38.03% of these workers make this level or below in hourly wage. Because our imputed labor cost measure is an upper

³⁷Note that we are assuming that most undergraduate workers employed by a grant are earning the same hourly wage.

³⁸The estimated coefficient is not statistically distinguishable using a *t*-test (*p*-value of 0.97).

bound on the true labor costs, these percentages are likely a lower bound on the share of undergrads who earn at or less than the minimum wage.

Using the same dataset, we also show that increases in the minimum wage translate into similar increases in labor costs for grants that continue employing the same number of undergraduates. By definition, labor costs are equal to wage times the hours worked, which we denote as $L_{it} = W_{it} \times H_{it}$ with W_{it} as the wage of undergrads working on grant i at time t , H_{it} as the hours worked, and L_{it} as the total labor cost. Our approach for this analysis runs a regression on the log-transformation of that equation and replaces W with the minimum wage.³⁹

Table A2 shows the results of regressing the log of labor costs divided by hours worked on the log-minimum wage. We get an estimate on the log-transformed minimum wage of 1.353. This indicates that a 1% increase in the minimum wage is associated with a 1.353% increase in the labor costs after controlling for the number of hours worked by undergrads. While this estimate is somewhat higher than 1, the estimate shows that the two variables have a strong positive association. We also include an estimate of the change in number of employees on these grants using a Poisson regression in the second column. This result shows a similar elasticity to the one we get for our main sample. Using these two measures together implies an own-wage elasticity of $-0.635/1.353 = -0.469$.

Table A2. Elasticity of Labor Cost per Hour and Minimum Wage

	Ln(Labor/Hours) OLS	Emps. UG Poisson
Ln(Mwage)	1.353*** (0.135)	-0.635*** (0.309)
N	9,115	9,115
R2	0.67	0.01
Dep. Mean	2.74	1.56

Taken together, this analysis demonstrates both that the wages of undergraduate workers are likely to be close to the minimum wage and that changes in the minimum wage are associated with increases in the cost of employing an undergraduate worker. We cannot say that individual undergrads earned a specific wage or what fraction of undergraduate workers at each university earned the minimum wage. Furthermore, we cannot say that the minimum wage is strictly binding for these workers. For example, it may be that undergraduate research assistants earned less than minimum wage, because they are not legally mandated to earn above the minimum wage, but the minimum wage impacts the outside option for these workers, thus making their wages and the minimum wage

³⁹Note that the actual wage earned by undergraduate workers might not be exactly the minimum wage. Therefore, it would be more accurate to think of the data generating process as $\ln(L_{it}) = \ln(MW_{it} + \delta_{it}) + \ln(H_{it})$, where MW is the minimum wage and $W_{it} = MW_{it} + \delta_{it}$. We could then transform that into the regression that we are able to run: $\ln(L_{it}) = \ln(MW_{it}) + \ln(H_{it}) + \epsilon_{it}$ where $\epsilon_{it} = \ln(1 + \delta_{it}/MW_{it})$. As this portion is not observable and yet correlated with the minimum wage, there is likely to be bias in the coefficient on log-minimum wage. If, as we showed in Table A1, the wage is very close to the minimum wage then this unobserved term may be small.

correlated. Instead, the above analysis shows that regardless of whether or not the minimum wage is strictly binding, the wages of these workers are correlated with changes in the minimum wage.

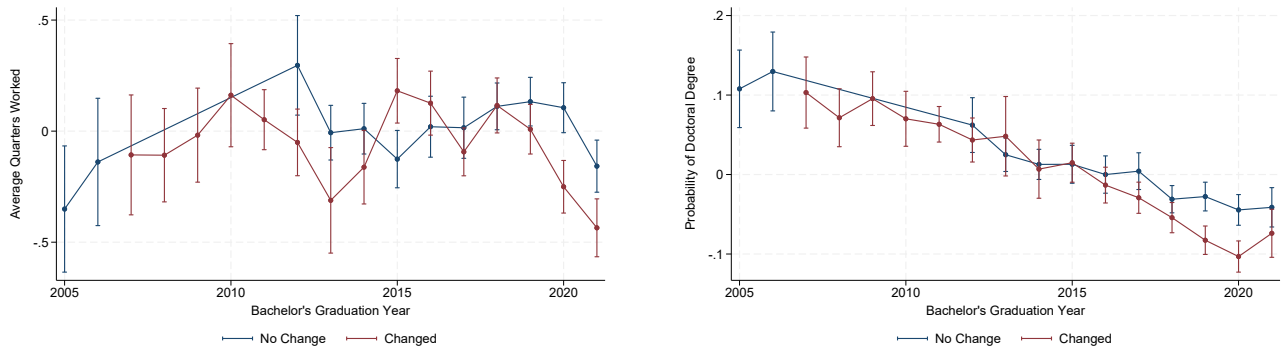
There are a number of limitations to these analyses. Our measure of the labor costs of a grant are likely to be noisy since we do not observe all non-labor expenses charged to grants. This measurement error in the dependent variable of the hedonic regression may result in less precision in the estimate. Furthermore, our measure of labor pay may be inaccurate if, for accounting reasons, the charges to a grant and the employment on a grant do not align within the same month. For example, if an employee was recorded to have worked from June through August, but the charges for that employment only posted in September then the imputed labor pay and the hours of work would not align and could create misleading estimates of the wage. Finally, only some universities provide data on the full-time status of undergraduate employees, that we can only apply this analysis for a subset of the universities in our sample.

E Non-Parametric First-stage and Reduced Form for Analysis of Minimum Wage as an Instrument for Pursuing a Doctoral-Level Degree

In this section, we provide non-parameteric visualization of our instrumental variable approach analyzing the effect of changes in the time spent working in university labs on pursuing doctoral-level degrees. Below, we show the first-stage by plotting the average number of quarters workers in university labs from our Student Outcomes Dataset after residualizing by university. We plot these points separately for students who experienced a minimum wage change during their time as undergraduates versus those that did not and across cohorts based on year of graduation. We remove the university fixed effect as some universities may have students more inclined towards graduate education regardless of work in labs or minimum wage changes. Similarly, below, we plot the probability of students pursuing a doctoral-level degree. Again, we residualize by university and show these probabilities separately for students who experienced minimum wage changes versus not.

Both plots are noisy, however, they confirm the analysis in the regressions show in Columns (2) and (4) of Table 11.

Figure A7. Non-parametric Evidence of First Stage and Reduced Form



(A) First Stage

(B) Reduced Form

Note: The above figures plot the first stage and reduced form of Equation 2 Equation 3 using the Student Outcomes Dataset. Both plots are residualized by institution fixed effects. The points are plotted according to the year a student graduated from their bachelor's degree. The plots are split according to whether or not the students experienced a minimum wage changed during their undergraduate years.

F Additional Instrumental Variable Analyses

In order for the minimum wage to serve as a valid instrument in our analysis of the effect of undergraduate employment in labs on pursuing a doctoral degree, the exclusion restriction must hold.

One way in which the exclusion restriction could be violated would be if following the increase in the minimum wage, the composition of which students worked in labs changed. For example, if PIs increased their standards when hiring undergraduate research assistants in a way that correlated with likelihood of those undergraduates going on to doctoral programs. If true, the increase in the minimum wage would increase the probability of students going on to doctoral programs even though that effect was not occurring through the channel of exposure to lab work.

While our data does not provide us with complete or detailed data on the socioeconomic backgrounds of students or their academic performance, we construct three variables to help us test if compositional changes may influence our instrumental variable estimates. First, we flag if a student's bachelors degree record in Steppingblocks gives an indication that the student graduated with honors.⁴⁰ Second, we flag if a student's bachelors degree field is clearly in a STEM field. Third, we flag the students who have ever worked on an account associated with Federal Work Study. While these are noisy measures, controlling for them placates some of the dimensions of potential compositional changes.

We add each of these indicator variables as additional controls in our instrumental variable analysis. Column (1) of Table A3 repeats the same estimation as Column (7) of Table 11. Column (2) adds if the student is flagged as graduating with honors. Column (3) adds if the student is flagged as having a bachelors degree in a STEM field. The estimated 2SLS coefficient in both of these columns remains positive, significant, and of a similar magnitude. Column (4) adds if the student is associated with

⁴⁰We flag degrees where the title or degree field has keywords, such as "Honors," "cum laude," etc.

FWS, while Column (5) adds all these controls together. These columns show a positive, but attenuated and insignificant 2SLS estimate. Ultimately, these regressions demonstrate that at least some of the minimum wages correlation with students pursuing doctoral level degrees may derive from compositional changes in which students work in labs rather than exclusively from changes in exposure to lab work induced by the minimum wage changes.

Caution should be taken, however, in interpreting these regressions. A student achieving Honors or pursuing a degree in STEM may be influenced by time spent working in a lab. Therefore, controlling for this outcome may in fact be conditioning on a collider.

Table A3. Effect of Minimum Wage Changes on Undergraduates Career Outcomes

	Doctoral Degree				
	(1)	(2)	(3)	(4)	(5)
Qtrs Worked	0.103*** (0.016)	0.103*** (0.016)	0.099*** (0.019)	0.079 (0.054)	0.082 (0.053)
Honors		0.129*** (0.029)			0.125*** (0.026)
STEM			0.055*** (0.015)		0.059** (0.024)
FWS				-0.058 (0.069)	-0.041 (0.063)
Constant	0.233*** (0.029)	0.228*** (0.028)	0.200*** (0.026)	0.271*** (0.088)	0.220*** (0.071)
N	28,283	28,283	28,283	28,283	28,283
Inst FE	Yes	Yes	Yes	Yes	Yes
Grad Yr FE	Yes	Yes	Yes	Yes	Yes
R ²	.	.	.	.	.
Dep. Mean	0.17	0.17	0.17	0.17	0.17
F	.	.	.	.	.

Standard errors in parentheses

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

Note: The above table shows the results of estimating the 2SLS model in Equation 3. Column (2) includes an indicator for the student's bachelors degree mentioning honors. Column (3) includes an indicator for the student's bachelors degree being in STEM. Column (4) includes if the student was ever paid on an account associated with Federal Work Study. Column (5) includes all these controls together. Fixed effects are included for the institution and the year of graduation. Standard errors are clustered at the university level.

We also investigate the exclusion restriction by running a placebo test. In this analysis, we regress

whether or not students pursued a doctoral level degree on minimum wage changes that occurred in the years after they graduated. Because our minimum wage data ends in 2020 and we wish to look at minimum wage changes in the three years after graduation, we use the sub-sample of students who graduated college between 2000 and 2016 for this analysis.

Table A4 shows the results of these regressions for one, two, and three years after graduation. Across all of these specifications, we find insignificant results. These coefficients contrast with the reduced form evidence that we provided in Table 11. These results also provide supportive evidence that there is not a direct effect of minimum wage changes on the pursuit of doctoral level education that occurs through a different pathway than the impact on the work performed as an undergraduate.

Table A4. Placebo Test of Minimum Wage Changes After Graduation from College

	Doc. Deg.		
	(1)	(2)	(3)
MWage Yr5	0.003 (0.005)		
MWage Yr6		-0.011 (0.008)	
MWage Yr7			-0.006 (0.011)
Constant	0.247*** (0.001)	0.250*** (0.002)	0.249*** (0.003)
N	15,699	15,699	15,699
Inst FE	Yes	Yes	Yes
Grad Yr FE	Yes	Yes	Yes
R2	0.02	0.02	0.02
Dep. Mean	0.25	0.25	0.25
F	0.30	1.65	0.30

Standard errors in parentheses

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

Note: The above table shows the results of estimating whether or not a students' pursued a doctoral level degree on prominent minimum wage changes in the years after they graduated from college. Fixed effects are included for the institution and the year of graduation. Standard errors are clustered at the university level.

G Balance Tables

The following tables show summary statistics for observations from labs at universities with large minimum wage changes vs smaller changes, graduate unions vs no unions, and high usage of undergrad workers vs lower usage.

Table A5. Balance Table of Labs Experiencing Small and Large Minimum Wage Changes

	Small Change	Large Change	<i>t</i> -stat	<i>p</i> -value
PI Female	0.22	0.21	0.51	0.61
PI Age	47.52	48.31	-3.50	0.00
Grants	2.06	2.39	-11.95	0.00
Direct Expend	98,049.05	111,366.90	-4.67	0.00
Vendor Spend	12,266.23	16,054.91	-5.53	0.00
Postdocs	0.54	0.64	-5.14	0.00
Grads	1.55	1.90	-8.37	0.00
UGs	1.03	1.30	-7.60	0.00
Staff	2.50	3.37	-8.76	0.00
N Labs	6503	4874		

Note. The above table shows the average attributes of labs that experienced minimum wage changes that are greater than 5% versus labs that only experienced minimum wage changes less than 5% during our sample.

Table A6. Balance Table of Labs Using Undergrads Intensively

	Not Intense	Intense	<i>t</i> -stat	<i>p</i> -value
PI Female	0.21	0.21	0.09	0.93
PI Age	48.30	47.21	4.25	0.00
Grants	2.48	1.82	21.47	0.00
Direct Expend	126,486.98	74,286.17	16.56	0.00
Vendor Spend	17,062.25	8,957.41	10.61	0.00
Postdocs	0.70	0.38	15.56	0.00
Grads	1.80	1.49	6.68	0.00
UGs	0.64	2.01	-35.32	0.00
Staff	3.57	1.93	15.03	0.00
N Labs	5272	4095		

Note. The above table shows the average attributes of labs that use undergraduates intensively versus using other forms of labor.

Table A7. Summary Statistics of Lab Panel Observations at Universities With and Without Graduate Student Unions

	No Union	Union	<i>t</i> -stat	<i>p</i> -value
PI Female	0.21	0.23	-2.29	0.02
PI Age	48.41	47.36	4.71	0.00
Grants	2.19	2.22	-1.26	0.21
Direct Expend	106,194.82	101,481.20	1.67	0.10
Vendor Spend	13,211.99	14,520.33	-1.92	0.05
Postdocs	0.67	0.50	9.32	0.00
Grads	1.80	1.61	4.58	0.00
UGs	1.00	1.28	-7.77	0.00
Staff	2.56	3.17	-6.24	0.00
N Labs	5487	5890		

Note. The above table shows the average attributes of labs at universities with grad student unions versus those without in our sample.

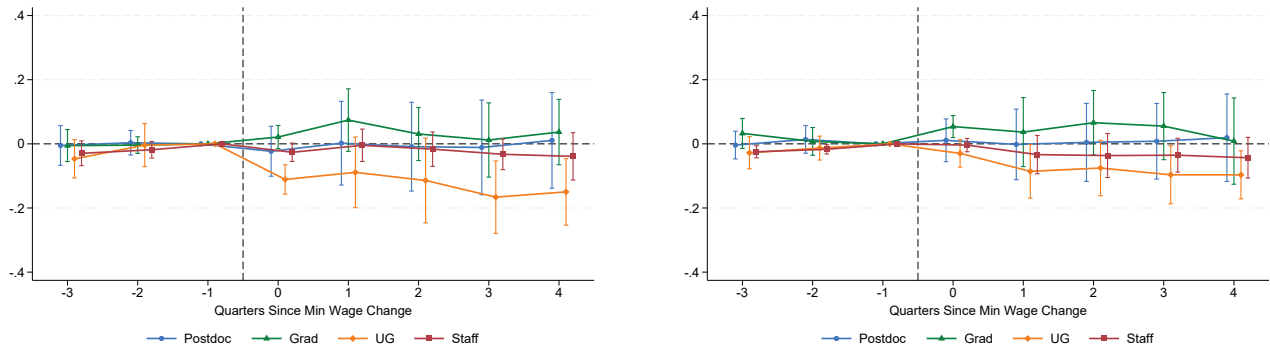
H Estimates using Indicators

The following figures and tables show the results of estimating the main labor effects using the following model:

$$E[Y_{ft}] = \sum_{j=-4}^5 \gamma_j D_{ft}^j + \mu_f + \mu_t + \delta \Omega_{ft} + \epsilon_{ft} \quad (4)$$

In this equation, the dependent variable Y_{ft} is the outcome of interest. The independent variables include D_{ft}^j , which is 1 when the minimum wage changed j periods in the future and 0 otherwise. We bin the end points by summing the minimum wage changes beyond the endpoints. We also include fixed effects for the lab, μ_f , as well as the time period μ_t . The variable Ω_{ft} includes fixed effects for the time period before, during, and immediately following minimum wage changes of less than \$0.25. Following [Cengiz et al. \(2019\)](#), we include these controls as such small changes in the minimum wage are unlikely to impact labs like larger minimum wage changes.

Figure A8. Main Effects Using Indicators

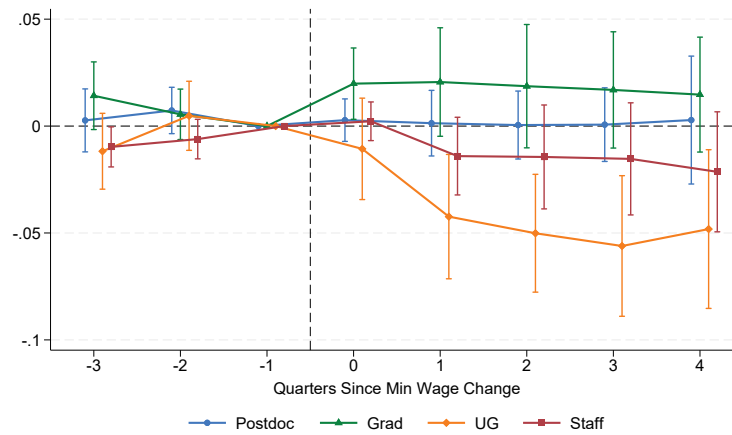


(A) Employee Days

(B) Distinct Employees

Note: The above figures plot the estimated coefficients from Equation 4 using a Poisson model and data from the Lab Panel. In Figure (a), the dependent variable is the number of days of employment. In Figure (b), the dependent variable is the number of distinct employees working in the lab in each quarter. Both of these figures plot the coefficients from estimating the equation separately by type of worker.

Figure A9. Probability of Employing Worker



Note: The above figures plot the estimated coefficients from Equation 4 using OLS and data from the lab-by-quarter Panel. The dependent variable is whether or not the lab employed at least one employee of each type of labor. The figure plots the coefficients from estimating the equation separately by type of worker.

Table A8

	(1) Emp. Days Poisson	(2) Emps. Poisson	(3) Employ OLS	(4) Days/Emp OLS	(5) Intensive Poisson
ΔQ	-0.126*** (0.047)	-0.077** (0.035)	-0.041*** (0.013)	-0.032 (0.021)	-0.048 (0.051)
ϵ	-0.126*** (0.047)	-0.077** (0.035)	-0.041*** (0.013)	-0.032 (0.021)	-0.048 (0.051)
N	264951	264951	264951	113443	113443
N Labs	11377	11377	11377	10441	10441
Lab FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
R2	0.54	0.39	0.32	0.38	0.60
Dep. Mean	86.35	1.19	0.43	4.20	201.05

Standard errors in parentheses

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

Note: The above tables displays the ΔQ and ϵ estimates based on estimating Equation 4 using data from the Lab Panel. In Column (1), the dependent variable is the number of days of undergraduate employment in labs estimated using a Poisson model. In Column (2), the dependent variable is the number of distinct undergraduates employed in labs estimated using a Poisson model. In Column (3), the dependent variable is an indicator for the lab employing at least one undergraduate estimated using OLS. In Column (4), the dependent variable is the log-transformed number of days per employed undergraduate in labs that employed at least one undergraduate estimated using OLS. In Column (5), the dependent variable is the number of days of undergraduate employment in labs that employed at least one undergraduate estimated using a Poisson model.

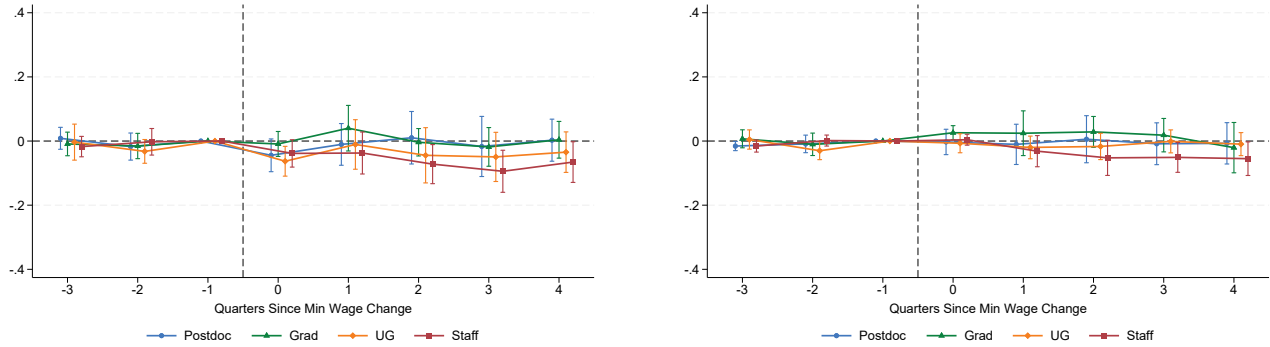
I Estimates Using Log Transformations

In this section, we present our main results using a variety of alternative specifications that leverage log transformed variables.

In addition to the event study approach, shown in Equation 1, we also estimate two-way fixed effects models. The specification for that model is the following:

$$E[Y_{ft}] = \beta \ln(mwage)_{ft} + \mu_f + \mu_t + \delta \Omega_{ft} + \epsilon_{ft} \quad (5)$$

Figure A10. Effect of Minimum Wage Changes on Employment Using Log-Transformed Days of Work



(A) Employee Days

(B) Distinct Employees

Note: The above figures plot the estimated coefficients from Equation 1 using OLS and data from the Lab Panel. The dependent variable is log-transformed days of work for employees of each type of labor. The figure plots the coefficients from estimating the equation separately by type of worker. Note that when the log-transformation is not defined then the observation is dropped.

Table A9. University Level Estimate of Elasticities

	(1)	(2)	(3)	(4)
	Share	Ln(Emps. UG)	Ln(Days UG)	Ln(Days/Emps. UG)
Ln(MWage)	0.005* (0.003)	-0.520 (0.985)	-1.099 (0.996)	-0.579 (0.351)
N	1,945	1,945	1,945	1,945
Inst FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
R2	0.93	0.93	0.92	0.68
Dep. Mean	0.00	4.42	7.93	3.52
F	3.60	0.28	1.22	2.72

Standard errors in parentheses

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

Note: The above table displays the estimates from running OLS regressions on observations of universities-by-quarter. In Column (1), we regress the share of undergrads who work in a lab on the log-transformed state minimum wage for that university. This is computed as the number of undergrads working in labs in our data divided by the total fall enrollment of that university. In Column (2), we regress the log-transformed number of distinct undergrads working in a lab. In Column (3), we regress the log-transformed number of days of work by undergrads. Finally, in Column (4), we regress the log-transformed days of undergrad work divided by the total distinct undergrad workers.

Table A10. Two-way Fixed Effects Estimates of the Effect of Minimum Wage Changes Using Poisson

	(1) Emp. Days Poisson	(2) Emps. Poisson	(3) Employ OLS	(4) Days/Emp OLS	(5) Intensive Poisson
ln_mwage_state	0.046 (0.161)	0.347* (0.201)	0.110 (0.064)	-0.124** (0.054)	-0.239*** (0.087)
N	264951	264951	264951	113443	113443
N Labs	11377	11377	11377	10441	10441
Lab FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
R2	0.54	0.39	0.32	0.37	0.60
Dep. Mean	86.35	1.19	0.43	4.20	201.05

Standard errors in parentheses

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

Note. In the above table, we display the results from running a Poisson regression estimating Equation 5 using observations from the Lab Panel Dataset.

Table A11. Two-way Fixed Effects Estimates of the Effect of Minimum Wage Changes Using OLS

	(1) Emp. Days OLS	(2) Emps. OLS	(3) Employ OLS	(4) Days/Emp OLS	(5) Intensive OLS
ln_mwage_state	-0.126 (0.082)	-0.030 (0.093)	0.110 (0.064)	-0.124** (0.054)	-0.126 (0.082)
N	113443	114649	264951	113443	113443
N Labs	10441	10451	11377	10441	10441
Lab FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
R2	0.49	0.53	0.32	0.37	0.49
Dep. Mean	4.86	0.66	0.43	4.20	4.86

Standard errors in parentheses

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

Note. In the above table, we display the results from running an OLS regression estimating Equation 5 using observations from the Lab Panel Dataset. In these specification, we log transform the dependent variables.

Table A12

	(1) Log Emp. Days OLS	(2) Log Emps. OLS	(3) Employ OLS	(4) Log Days/Emp OLS	(5) Log Intensive OLS
ΔQ	-0.040 (0.028)	-0.011 (0.013)	-0.041*** (0.013)	-0.032 (0.021)	-0.040 (0.028)
ϵ	-0.040 (0.028)	-0.011 (0.013)	-0.041*** (0.013)	-0.032 (0.021)	-0.040 (0.028)
N	113443	114649	264951	113443	113443
N Labs	10441	10451	11377	10441	10441
Lab FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
R2	0.49	0.53	0.32	0.38	0.49
Dep. Mean	4.86	0.66	0.43	4.20	4.86

Standard errors in parentheses

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

Note: The above tables displays the ΔQ and ϵ estimates based on estimating Equation 1 using data from the Lab Panel. In Column (1), the dependent variable is the log-transformed number of days of undergraduate employment in labs estimated using OLS. In Column (2), the dependent variable is the log-transformed number of distinct undergraduates employed in labs estimated using OLS. In Column (3), the dependent variable is an indicator for the lab employing at least one undergraduate estimated using OLS. In Column (4), the dependent variable is the log-transformed number of days per employed undergraduate in labs that employed at least one undergraduate estimated using OLS. In Column (5), the dependent variable is the number of days of undergraduate employment in labs that employed at least one undergraduate estimated using OLS. Note that when the log-transformation is not defined then the observation is dropped.

Table A13. Effect of Minimum Wage Changes on Scientific Paper Production

	(1) WoS Publications Poisson	(2) PubMed Publications Poisson	(3) 5 Year Citations Poisson
Ln(MWage)	-0.356 (0.549)	-0.003 (0.414)	-0.424 (0.942)
N	28676	55607	23949
N Labs	11377	11377	11377
Lab FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
R2	0.75	0.64	0.79
Dep. Mean	1.19	4.49	18.48

Standard errors in parentheses

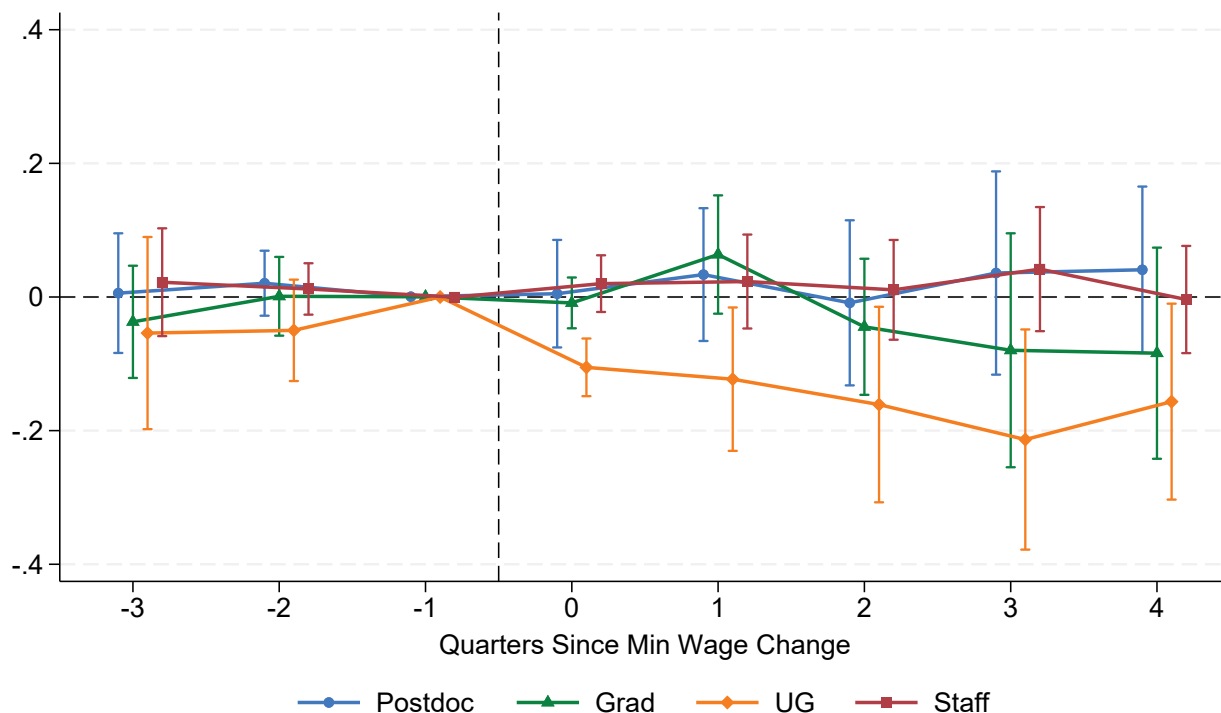
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The above tables displays the estimated coefficients from estimating Equation 5 using a Poisson model and data from the lab-by-year Panel. In Column (1), the dependent variable is the number of publications linked to grants from the lab published in the year and linked to Web of Science. In Column (2), the dependent variable is the number of publications linked to grants from the lab published in the year and linked to PubMed. In Column (3), the dependent variable is the number of publications linked to grants from the lab published in the year and linked to Web of Science and weighted by the number of citations to those publications in the five years after publication.

J Analysis of Potential Mean Reversion

If employment in labs has mean reversion around the time of minimum wage changes, this could make our estimates of the decrease in usage of undergraduate workers appear larger than it really is. In order to test for the influence of mean reversion, we estimate a linear trend on employment using data from before minimum wage events and then add that linear trend to our estimates of the effect of minimum wage changes using the full sample. We undertake this procedure using the Stacked Dataset, both because it provides the cleanest distinction between pre- and post- time periods and because it addresses potential forbidden comparisons and negative weights. The results are displayed below.

Figure A11. Event Study of Days of Employment Testing for the Influence of Potential Mean Reversion



Note: The above figures plots the estimated coefficients from estimating an event study using the Stacked Dataset. The procedure is similar to the one used for Figure 2(a), except that in this one, we include event-specific lab and year fixed effects in the regression.

K Known PI Sample

While our main sample examines the labs of all faculty members in the UMETRICS data that meet our criteria, we also analyze the sub-sample of labs associated with faculty who are known to be principal investigators of federally sponsored grants. IRIS matches UMETRICS data on faculty to the grant databases of NSF, NIH, DOE, DOD, and NASA using names and affiliations, which are not available to us. IRIS then provided us with a flag for which faculty in our anonymized data had appeared as a PI in those grant databases. The results in this section use only those labs.

Table A14. Main Effects Using Known-PI Sample

	(1) Emp. Days Poisson	(2) Emps. Poisson	(3) Employ OLS	(4) Days/Emp OLS	(5) Intensive Poisson
ΔQ	-0.147*** (0.044)	-0.112*** (0.033)	-0.028* (0.015)	-0.033 (0.021)	-0.089 (0.056)
ϵ	-1.721*** (0.520)	-1.315*** (0.385)	-0.332* (0.180)	-0.404 (0.251)	-1.084 (0.681)
N	161408	161408	161408	65336	65336
N Labs	6132	6132	6132	5651	5651
Lab FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
R2	0.52	0.38	0.32	0.34	0.57
Dep. Mean	79.58	1.08	0.41	4.23	196.09

Standard errors in parentheses

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

Note: The above table shows the results of estimating Equation 1 with Poisson. Standard errors are clustered at the level of the state of the university of the lab. The results are estimated based on the sub-sample of the Lab Panel Dataset where the PI can be linked to being an official PI on a NSF, NIH, DOE, DOD, and NASA grant.

L Grants without Employees

For the analysis in the main text, we restrict the grants associated with labs to be those that have at least one employees. This ensures that the labs in our main analysis are active research labs and not just administrative accounts. In the below table and figure, we remove that restriction.

Table A15. Main Effects for Grants with and Without Employees

	Summary Stats on Compliers	
	output_mat	
	Whole Sample	Compliers
Female	.44811	.7770851
BA STEM	.713821	.2556336
BA Honors	.0330941	.0587996
FWS	.1345685	.5582388

Note: The above table shows the results of estimating Equation 1 with Poisson. Standard errors are clustered at the level of the state of the university of the lab. The results are estimated based on the sample of all grants regardless of whether or not they employ an employee.

M Bootstrapped Errors

In the below results, we estimate our main labor results using bootstrap standard errors.

Table A16. Effect of Minimum Wage Changes on Labor with Bootstrapped Standard Errors

	(1) Emp. Days Poisson	(2) Emps. Poisson	(3) Employ OLS	(4) Days/Emp OLS	(5) Intensive Poisson
ΔQ	-0.104 (0.106)	-0.074 (0.097)	-0.027 (0.018)	-0.015 (0.063)	-0.053 (0.097)
ϵ	-1.256 (1.272)	-0.886 (1.165)	-0.323 (0.217)	-0.188 (0.776)	-0.653 (1.196)
N	264951	264951	264951	113443	113443
N Labs	11377	11377	11377	10441	10441
Lab FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
R2	0.54	0.39	0.32	0.38	0.60
Dep. Mean	86.35	1.19	0.43	4.20	201.05

Standard errors in parentheses

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

*Note: The above table shows the results of estimating Equation 1 with Poisson.
For the standard errors, we used bootstrapped standard errors, clustered by state
of the university of the lab, with 50 replications.*