The Effects of Minimum Wage Changes on University Research Labs and Scientific Careers*

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Abstract

We study the effect of minimum wage changes on the employment and career trajectories of undergraduate research assistants in university labs. Using administrative data from thousands of research labs and a difference-in-differences framework, we find that scientists employ 7.1% fewer undergraduates in their labs following minimum wage increases, while increasing employment of graduate students. Using an instrumental variable approach, we estimate that undergraduate research assistants who experience minimum wage increases graduate with 11.6% fewer quarters of lab employment and pursue doctoral education at significantly lower rates. This effect is attenuated for students funded through Federal Work Study. *JEL codes:* I23, J30, O30.

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1 Introduction

A large literature examines how firms respond to changes in the cost of labor inputs, such as minimum wage increases (e.g. 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 W Risch, 2024). Despite the critical role of scientific research in driving innovation and economic growth, relatively little is known about how labor market policies affect university research laboratories. Existing estimates of labor cost changes on employment may not directly apply to university labs, which operate differently from traditional firms. The production of scientific knowledge in university labs is unique in that much of the labor—including postdocs, graduate students, and undergraduates—are both an input to the production of scientific research and an output. While principal investigators (PIs) seek to advance knowledge through their research, they are also responsible for training the next generation of scientists at their institutions. Additionally, unlike firms, university labs cannot pass higher labor costs onto consumers, as their primary outputs, such as scientific publications, are not priced (Leung, 2021). Recent evidence suggests that firms often absorb minimum wage increases through productivity gains and price pass-through, adjustment channels that are largely unavailable to university labs with non-market outputs and fixed budgets (Dube and Lindner, 2024; Rao and W Risch, 2024).

In this paper, we examine the effect of changes in labor costs that result from increases in state minimum wage laws on university lab employment. As many student employees at universities earn low wages, often at or near the minimum wage, such labor cost increases can impact lab hiring and personnel decisions.[1] We use rich administrative data from the accounting records of thousands of labs at U.S. research universities (UMETRICS) in a difference-in-differences event study design. This allows us to compare research labs' employment decisions when facing increases in the minimum wage due to state minimum wage law changes with labs facing stable labor costs at the same time.

We first estimate the short-run effects on employment in labs, and then turn to the longer-run effects on the funding of labs and the exposure of lab trainees to scientific work and career outcomes. For the short-run effects, we examine how PIs respond to higher labor costs in the year following a minimum wage change. PIs have fixed budgets that are set at the time that grants are awarded. If the price for one input increases, then PIs must either use less labor, possibly reducing output (publications), or substitute with another input. We estimate the employment effects of minimum wage changes on labor, including postdocs, graduate students, and undergraduate research assistants in labs and find that scientists employ 7.1% fewer undergraduate research assistants in response to minimum wage changes. The significant change is likely reflective of the fixed budgets facing PIs in the short-term and their inability to pass through costs, thus the relatively high elasticity is not entirely surprising. We find especially pronounced declines in demand among labs that employed more undergraduates prior to the minimum wage change. In addition, we highlight that labs slightly increase their use of graduate student labor, suggesting that some tasks previously done by undergraduates may be shifted to graduate students.

These findings are in line with recent work showing larger negative employment effects of mini-

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

mum 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.

We also examine the longer-run effects on lab funding and student trainee exposure to research experience. In the longer run, PIs can apply for more funding to compensate for the increased labor costs. Indeed, we find that PIs funded by the National Institutes of Health (NIH) are 27.82% more likely to utilize supplemental funding, additional funds provided 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 $150 million dollars in additional funding per year to fully restore employment in university labs.

The increased labor costs also impact student trainees' exposure to scientific work and career paths. We show that undergraduates at universities that experienced minimum wage increases worked 11.6% fewer quarters in labs during their college years. However, this effect was less pronounced for students participating in the Federal Work-Study program, which subsidizes wages for students with financial need. Lastly, leveraging minimum wage increases as an instrument variable for the time employed in labs, we document 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 after graduation. We find that working one more quarter in a lab during an undergrad's college years translates into a 10.5-11.3 percentage point increase in the rate of enrolling in a doctoral program.

Our findings contribute to two primary strands of literature. First, we add to the economics of science and innovation literature on knowledge production and the scientific workforce. Previous work on the responses of scientists to changes in inputs to scientific production have estimated the long-run impacts of the destruction of physical and human capital (Waldinger, 2016; Baruffaldi and Gaessler, 2018) 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) and increases in overall funding for research labs (Myers, 2020). Unlike the physical destruction of tangible assets or the death of collaborators, where an input becomes unavailable, 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 works are closely related to our own. Goolsbee (1998) demonstrates that changes in wages show little effect on the labor supply of R&D workers. However, this work focuses on the labor supply choices of these highly skilled individuals, while our work focuses on the labor demand of trainees. Furman and Teodoridis (2020) examine how a sudden price decrease in a single input to computer vision research induced established computer scientists to work on research utilizing that input. In our study, instead of looking at physical input costs and established researchers, we focus on a price change in the relative cost of different types of labor and examine the impact on scientific trainees. While it is clear from prior work in the economics of science and innovation about the important role of trainees like students and postdocs in the research production process, 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 rigorously examined in the literature.

Second, we provide new evidence for the labor economics literature on the impacts of the minimum wage. 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, which provide 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, 2022*a*,*b*). The records in this database are 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.[2]

For our analysis, we focus on transactions associated with research grants between 2000 and 2019.[3] Only grants that pay a faculty member are included. We exclude grants that fund whole centers or departments by excluding grants that pay more than 12 distinct faculty members[4] or that are NIH grants specifically meant for funding a research center.[5] Finally, the grants in our sample must both employ workers and make purchases from a vendor at some point during our sample time period.

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 of the preceding occupations.[6] For a limited set of PIs, we know information about which department they are employed in.

Finally, while UMETRICS does not provide the wages of individual workers, we impute a measure of the total labor costs of labs as a proxy for total income to workers by subtracting vendor and subaward costs from the direct costs of the labs (Harasztosi and Lindner, 2019).[7] Some labs do not have active grants or do not have 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 the Appendix.[8]

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

[2]Each 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/.

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

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

[5]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.

[6]We 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.

[7]This 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.

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

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 267,737 lab-by-quarter observations. As shown in Panel B of Table 1, the average lab spends $115,316.23, employs 1.17 undergraduate research assistants and employs 1.89 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.[9] 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 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 72,682 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.[10] 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

[9] We 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.

[10] IRIS, 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.

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. This enables us to say if students who remain employed in labs are more likely to work in higher or lower productivity labs.

This panel dataset contains 200,168 undergraduate-by-quarter observations for 25,021 undergraduate students. On average, as shown in Panel F of Table 1, 42% of the observations in this dataset are female undergrad RAs and 7% are FWS students. Across the dataset, 44% 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 decribed above. As outcomes, we flag if the Steppingblocks data list the individual as going on to a doctoral degree program, and if the individual lists employment in the life sciences industry. 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.[11] 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.

This dataset, which we refer to as the Student Outcomes Dataset, contains 34,568 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, 16% go on to complete a doctorate 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 0.70 quarters working in NIH sponsored labs.[12]

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

[11] We 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.

[12] The 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.

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 46 state-level minimum wage changes that occurred. Of those, 25 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. At the university-level, this creates 43 university-level minimum wage increase events. The average prominent minimum wage event led to an increase of 8.41%. The average minimum wage faced by a lab in our sample is $7.52.

2.3 Data Limitations

A limitation of the UMETRICS data is that it does not provide salary information for individual employees. Thus, we cannot directly observe what share of undergrads in our sample earn the minimum wage or the "bite" of the minimum wage increases.

Previous studies indicate that university student employees frequently earn a minimum wage.[13] Indeed, increases in minimum wage induce employers to switch to student and teenage employees (Lang and Kahn, 1998). Many university staff also receive minimum wage compensation. A survey conducted by the College and University Professional Association for Human Resources of a select set of universities found that in 2018, approximately 15% of technical and paraprofessional staff at universities earned minimum wage (Brantley, 2021). Lastly, for undergraduates seeking employment, the minimum wage often determines the wages of alternative sources of employment.

Some might still question if the wages of undergraduate research assistants are really affected by changes in the minimum wage. While our analysis leverages state minimum wage changes, we 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).[14] Figure A1 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 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.

In addition, in Appendix C, we show that the average wage of undergraduate research assistants

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

[14]The 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.

at the universities in the UMETRICS data is close to the minimum wage level. We also show that minimum wage increases are associated with similar-sized increases in the labor costs of grants after controlling for the amount of work performed on the grants. Taken together, these results provide evidence that the cost of undergraduate research assistants is connected to the minimum wage.

2.4 Descriptive Statistics

Figure 1 shows the effective minimum wage across universities in the sample. Figure A2 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 A3 shows when minimum wage changes occur. The majority of these changes occur during the first quarter of the year, however, a bit under 40% of the minimum wage changes occur in other quarters. In Figure A4, 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.

Labs vary in their employment of workers of different occupational levels. In Figure A5, 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 A6, 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:

$$E[Y_{ft}] = \sum_{j=-4}^{5} \gamma_j D^j_{ft} + \mu_f + \mu_t + \delta\Omega_{ft} + \epsilon_{ft} \tag{1}$$

In this equation, the dependent variable Y_{ft} is the outcome of interest. The independent variables include D^j_{ft}, 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 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 $\Delta Q = \overline{D} * \frac{1}{5} \sum_{j=-1}^{4} \gamma_j$. 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: $\epsilon = \frac{1}{5} \sum_{j=-1}^{4} \gamma_j$.

It should be noted that because, for privacy reasons, our data does provide the actual salary or earnings of individuals, we do not know if the minimum wage was binding for all the undergraduate employees in our sample, or the "bite" of the minimum wage changes in our sample. We, therefore, are not able to calculate the own-wage elasticity (OWE) of employment discussed by Dube and Zipperer (2024), which reflects how employment for a specific group (undergrad RAs in our case) responds to an increase in the average wage of that group induced by the minimum wage change.

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.[15] Table A3 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.

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.[16] 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 to address any concerns about the how the weights of the staggered setup may be impacting our results, we leverage the approach of de Chaisemartin and D'Haultfœuille (2020). The advantage of this approach is that it can account for when a minimum wage changed multiple times by focusing on comparisons between the labs that experienced minimum wage changes with those that did not in the same time period. Intuitively, along with the variation in the magnitude of the minimum wage changes, these are the comparisons that we wish to leverage for identification. One caveat is that this approach assumes that a lab's potential outcomes for a current change in the minimum wage does not depend on previous minimum wage changes, known as the "no carryover" assumption (Roth et al., 2023). This assumption, however, may not be restrictive in this context, since many decisions

[15] For 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.

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

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. Finally, the consistency of results across our 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.

3.2 Instrumental Variable Analysis of Student Career Outcomes

We next turn to examining how students' research experience in labs impacts their career outcomes, focusing on pursuing a graduate degree and entering a scientific career. Since the relationship between time spent working in labs and subsequently working in scientific careers is likely endogenous, we use a change in the minimum wage as an instrumental variable, which provides exogenous variation in employment in labs among otherwise similar students. This allows us to isolate the causal effect of research work experience on subsequent career outcomes. We estimate the following two-stage least squares regressions:

$$E[Exper_i] = \beta MWageChanged_{jt} + \mu_j + \mu_t + \delta\Omega_{it} + \epsilon_i \tag{2}$$

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

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 restriction. 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.

For the exclusion restriction to hold, it must be that changes in the minimum wage during the time that a student is in college only impact their decision to pursue a graduate degree or a science career through the channel of the time they spent working in university labs. One possibility would be if the change in minimum wage directly changed the appeal of employment opportunities beyond going to 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.[17] Another possibility is that the increase in the minimum wage increases the income of undergrads such that the additional earnings make graduate studies more affordable for them. 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 8.4% and students worked 1.46 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 ($8.91), this would only translate into an increase of approximately $131.13 by the end of their college years, which seems too small to significantly impact their decision through this channel. Additional data, such as students' financial information, would be required to rule out all these channels.

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. 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 7.2% 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. Two quarters after a minimum wage change, the average lab increased their use of graduate labor by 12.3%.

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 postdocs employment changed after a minimum wage change.

Figure 2A demonstrates a number of important results. First, the 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

[17] The 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

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 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 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 3.1 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 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.[18]

4.2 Heterogeneity across labs

In Table 3, we explore the heterogeneous effects of the minimum wage changes by estimating Equation 1 on different types of labs. Columns (1) and (2) show the results for labs considered "not-intensive" and "intensive" in their use of undergraduate research assistants, respectively. The estimated change in the use of undergrad time for the not-intensive labs is negligible and not significant, while the decrease in the usage of undergraduate labor for intensive labs is of similar magnitude to the overall effect previously estimated. We confirm this by also estimating the event study, Equation 1, split by not-intensive vs intensive labs and plotting the coefficients in Figure 4. This finding aligns with labs that heavily utilize undergrad time being more sensitive to changes in the labor cost, while labs with minimal or no usage of undergrad time largely ignoring the input price change.

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 utilize undergraduate research assistants more intensively, including biology and psychology labs, are particularly impacted by the labor cost increase. In addition, our results show that some funding agencies may provide more leeway for dealing with increased costs than other funders.

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, 0.075, 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

[18] As noted earlier, we unfortunately cannot calculate the own-wage elasticity that been discussed in the recent minimum wage literature by Dube and Zipperer (2024) in our analysis because we do not observe the actual wages of the workers in our dataset.

coefficient is not statistically significant. These results indicate that the time that grad students work in labs increase, 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 the work of graduate students splitting our sample between universities with and without graduate student unions. We find that both sets of schools show the positive uptick in the use of graduate student labor following the minimum wage change. This is somewhat surprising as one might have expected that there would be less substitution to graduate labor for tasks that had previously been done by undergraduates in schools with unions, as collective bargaining agreements might protect graduate students from doing additional tasks. On the other hand, if universities with grad unions are also the universities in which graduate student workers more central to the work in labs, then it is possible that the uptick simply reflects the importance of graduate students on those campuses.[19]

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 minimum wage changes occur around the same time when the grants supporting labs expire, this could create a spurious correlation between minimum wage changes and the decline in employment in a lab.

In Table 5, we add a control variable to Equation 1 indicating if one of the grants funding a lab was in its final quarter. This will account for whether a lab is winding down one of its grants. Column (1)-(3) demonstrates that the estimates with this additional control are similar to those found in Table 2. Thus, it is unlikely that the life-cycle of funding for labs is driving this result.

Second, it is possible that different universities had different patterns regarding employment. For example, it is possible that some universities were increasing their involvement of undergraduate students in research labs while other universities might have been shifting away from using undergraduate RAs. If minimum wage changes correlated systematically with these patterns, we may get biased estimates of the effect of the minimum wage changes on employment. Therefore, in Columns (4)-(6), we add in separate time trends for each university. We do that in addition to including the fixed effect for the lab having a grant ending in a quarter. The results are not fundamentally different.

Third, recent insights into staggered difference-in-difference models have revealed the need to carefully understand the heterogeneity across events when interpreting the results of TWFE and event study models (Meer and West, 2016; Roth et al., 2023). While our main analysis using Equation 1 is not a typical difference-in-difference, since it utilizes both the variation in the timing and the magnitude

[19] Appendix Table A5 displays the mean attributes of lab-by-quarter observations for labs at universities with and without graduate student unions.

of the minimum wage changes, we nevertheless take steps to check the robustness of our findings.

In order to address concerns about how these varying weights might impact our estimates, we re-estimate our main effects using the procedure of de Chaisemartin and D'Haultfœuille (2020) (hereafter DCDH). This procedure make comparisons between labs experiencing minimum wage increases and labs that did not experience minimum wage changes at the same time. Because the DCDH procedure results have only been probed using OLS regressions, we use this procedure with dependent variables of inverse hyperbolic sine (IHS) transformed number of days of undergraduate labor, IHS transformed number of undergraduate workers, and an indicator for if a lab employed at least one undergraduate worker. In addition, following the advice of Roth (2024), we use long-differences for both pre-treatment and post-treatment in order to make the event study plot similarly interpretable to one from a TWFE.

The estimated coefficients on the leads and lags from this procedure are plotted in Figure 5, and the point estimates are also listed in Table 6. While the estimated effects are less precisely estimated, the general pattern remains. In the quarters prior to the minimum wage change, the estimates are close to zero. In the quarters following the minimum wage change, the estimates shift to be consistently below zero although not always statistically significant. While these estimates are considerably more noisy and the changes less pronounced, the overall pattern is consistent with our results from the generalized difference-in-difference based on Poisson TWFE in Equation 1.[20]

Lastly, lab level analysis may obscure the changes going on at the project level. While we perform our main analysis at the lab-level, as we assume that there is some fungibility of funding across a PI's projects, if our mapping of grants to labs is incorrect it may impact the estimated treatment effect. In order to demonstrate that this is not a concern, we re-run our main analysis using grant-by-quarter panel as well.[21] The 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.

We take these robustness checks to be reassuring that our findings are not driven by the empirical framework or the life-cycle of sponsored research funding.

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.[22] Column (1) uses the number of WoS publications associated to 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 5 year forward citations. Across all

[20] Differences from our main specification may also arise because of the transformation of the dependent variable, weighting of the comparisons during aggregation, and the comparisons made in each procedure.

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

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

of the specifications, the coefficients are small and not statistically significant.[23]

We believe that this implies that while there may be some adjustment costs due to the change in the minimum wage, the overall effect on scientific production is likely to be minor in the short-run. More research—requiring a longer panel of data—will be required to understand if the change in the personnel working in the lab 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 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. While the estimate is positive, it is not statistically significant. This implies that on average it may be hard for labs to get 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.[24] The estimated coefficient on the probability of a supplement in the quarters following the minimum wage change increases by 0.5 percentage points or 27.82% 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.

[23] In Table A11, 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.

[24] `https://grants.nih.gov/funding/funding-categories/supplemental-funding`

We interpret these results to mean that PIs either have limited options in changing their subaward 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 2.7 percentage points or 6.14% 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.

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 with the undergraduate student having ever been paid on an account associated with Federal Work-Study (FWS) students. The interaction term is positive and significant implying that FWS students may be more likely to continue working as research assistants even after a minimum wage change. This could be because FWS subsidizes the cost to 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. 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 coefficients. The positive coefficient on the minimum wage changing indicates that students who remain employed worked in labs that produce more papers per year than the labs that they had worked in prior to the minimum wage change. This could indicate that students who continue working in labs find their way towards higher production labs or that the labs that continue hiring students after a minimum wage increase tend to be the more productive labs.

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 from FWS backgrounds may be less impacted, which implies that students from less affluent backgrounds are not being differentially negatively impacted. This loss in exposure to scientific labs, however, may impact career choices later. Finally, students who continue being employed tend to be employed in labs that produce more scientific publications.

4.8 Effect 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. The estimated coefficient of 0.008 is statistically significant and implies that working one more quarter is correlated with a 0.8 percentage point higher rate of enrolling in a doctoral program. Relative to the unconditional probability of enrolling in these programs, this is equivalent to a 4.66% higher rate.

Columns (2) and (3) provide first-stage regressions 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 -0.167 and significant. 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 9.63, which may indicate a weak instrument. The estimates in Column (3) show negative and significant coefficients for the indicators of minimum wage increases during students' first, second, and third years. The estimated coefficient on the minimum wage change in the senior year of college is positive but not statistically significant. The F-statistic on this model is 38.25.

Columns (4) and (5) show the reduced-form regressions for these instruments. Again, the single instrument version in Column (4) shows a negative and significant coefficient, implying that minimum wage increases are associated with a decreased probability of going on to doctoral programs. 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 third year, and a positive and significant coefficient in the final year.

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 0.105 and 0.113 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 10.5-11.3 percentage points. Relative to the unconditional probability of enrolling in a doctoral program, these estimates suggest a 65-70% increase in the rate of pursuing doctoral programs.

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 0.025 and 0.016 and significant at the $p < 0.1$ 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.

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 and not 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 three years of college. The F-statistic on the single and multiple instrument first-stage regressions are 19.96 and 63.48. 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 0.024 and 0.017 and significant at the $p < 0.05$ and $p < 0.01$ levels respectively. 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. 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. We hope that in the future, universities will provide more detailed data to allow for a deeper examination of these questions.

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.[25] 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 for the minimum wage increase for all of their undergraduate research assistants, the total cost would be on the order of $10.04 million per year. For funding agencies to compensate only the labs for the share of undergraduate labor that typically declines following a minimum wage increase, the total would be approximately $2.32 million per year. In 2019, the universities in our sample enrolled approximately 1 million undergraduate students in 2019. The total number of undergraduate students enrolled in U.S. universities in that year was 15 million. Assuming similar rates of students participating research across all universities in the country, the total cost to compensate for all the undergrad research assistants may be on the order of $150 million per year.

While these figures seems small relative to the total budgets of U.S. scientific funding agencies, our

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

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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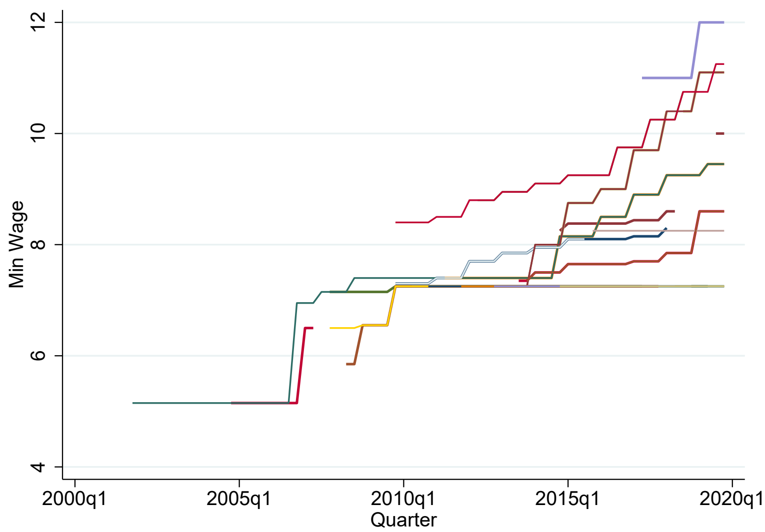
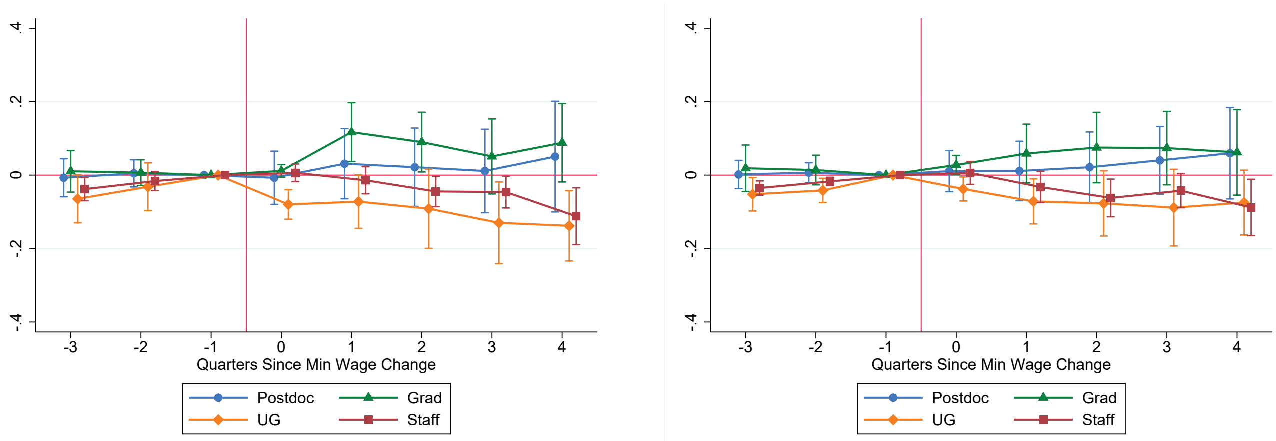
6 Figures and Tables

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.

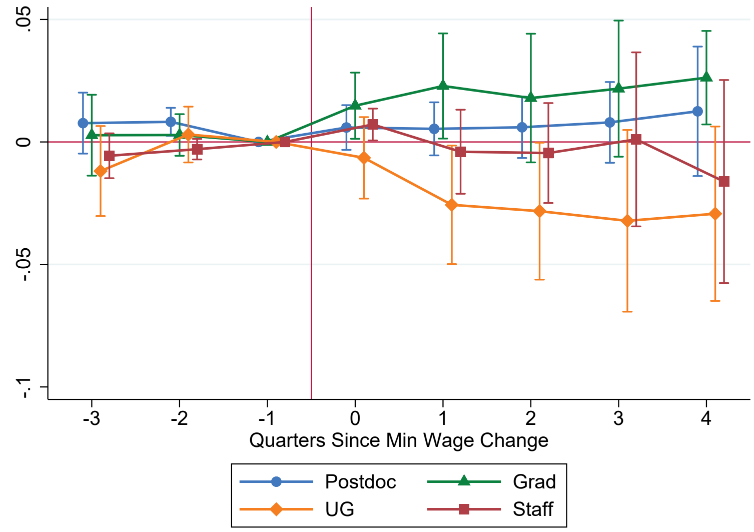
Figure 2. Main Effects Poisson Regressions



(A) Employee Days **(B)** Distinct Employees

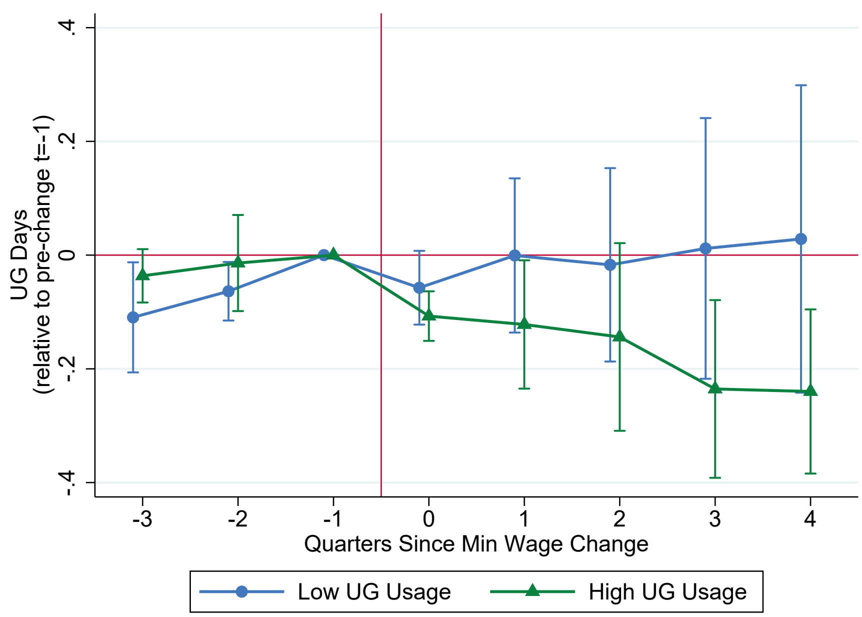
Note: The above figures plot the estimated coefficients from Equation 1 using a Poisson model and data from the Lab Panel. In Figure (a), the dependent variable is the number of days of employment. In Figure (b), the dependent variable is the number of distinct employees working in the lab in each quarter.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

Figure 3. Probability of Employing Worker



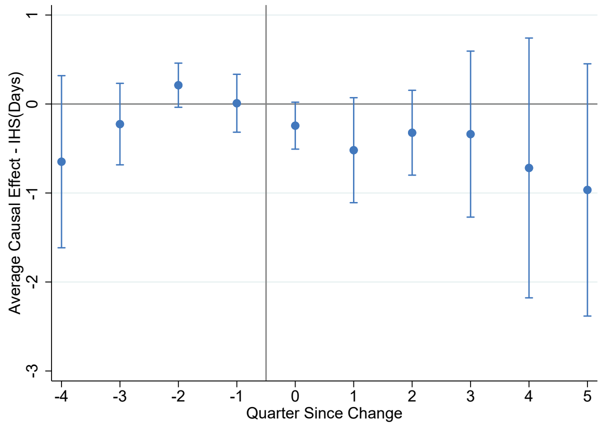
Note: The above figures plot the estimated coefficients from Equation 1 using OLS and data from the Lab Panel. The dependent variable is whether or not the lab employed at least one employee of each type of labor. The figure plots the coefficients from estimating the equation separately by type of worker.

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

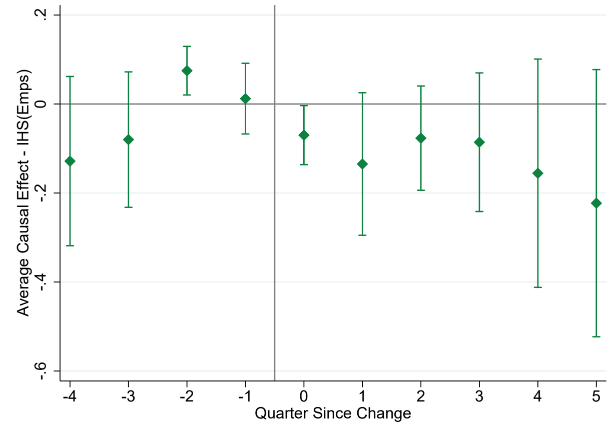


Note: The above figures plot event study estimates and confident intervals from Equation 1. The dependent variable is the log number of days of work performed by undergraduates plus one. The regression model includes grant and quarter fixed effects. Standard errors are clustered at the university level. 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%.

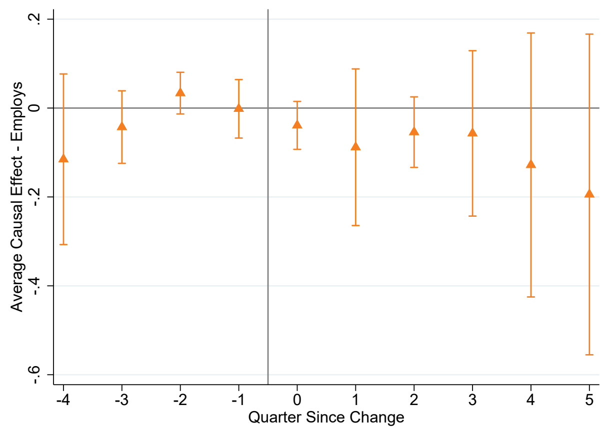
Figure 5. Staggered DiD Estimates Using de Chaisemartin and D'Haultfœuille (2020) Method



(A) Employee Days



(B) Distinct Employees



(C) Employed

Note: The above figures plots the estimated coefficients from estimating the de Chaisemartin and D'Haultfœuille (2020) procedure on observations from the Lab Panel. In Figure (a), the dependent variable is the IHS transformed number of days of undergraduate employment in a lab. In Figure (b), the dependent variable is the IHS transformed number of distinct undergraduate employees working in a lab. In Figure (c), the dependent variable is an indicator for the employment of at least one undergraduate employee in a lab.

Table 1. Mean Attributes of Observations in Dataset

	Mean	P25	P50	P75
Panel A: Labs (N=11,399)				
PI Female	0.22	0.00	0.00	0.00
PI Age	47.87	39.71	47.10	55.37
Known PI	0.54	0.00	1.00	1.00
Panel B: Lab Panel Dataset (N=267,737)				
PI Female	0.21	0.00	0.00	0.00
PI Age	48.45	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	115,316.23	29,324.08	65,877.79	135,120.81
Vendor Spend	16,017.13	200.00	3,472.00	13,851.06
Postdocs	0.66	0.00	0.00	1.00
Grads	1.89	0.00	1.00	3.00
UGs	1.17	0.00	0.00	1.00
Staff	3.50	0.00	2.00	4.00
Panel C: Grant Panel Dataset (N=184,966)				
Direct Expend	51,415.07	13,812.78	30,255.33	58,491.90
Vendor Spend	7,036.67	0.00	907.18	5,066.78
Postdocs	0.32	0.00	0.00	0.00
Grads	1.03	0.00	1.00	1.00
UGs	1.00	0.00	0.00	1.00
Staff	1.73	0.00	1.00	2.00
Panel D: Production Dataset (N=72,682)				
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=200,168)				
Female	0.42	0.00	0.00	1.00
Age	21.34	18.75	20.25	22.75
Fed Work-Study	0.07	0.00	0.00	0.00
Employed in Lab	0.44	0.25	0.38	0.63
Panel F: Student Outcomes Dataset (N=34,568)				
Female	0.46	0.00	0.00	1.00
Qtrs Worked	1.44	0.00	0.00	2.00
Qtrs Worked NIH	0.70	0.00	0.00	0.00
Doctoral Degree	0.16	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	-0.102***	-0.070*	-0.024**	-0.015	-0.053
	(0.039)	(0.036)	(0.012)	(0.015)	(0.038)
ϵ	-1.236***	-0.845*	-0.295**	-0.192	-0.661
	(0.469)	(0.438)	(0.146)	(0.182)	(0.467)
N	267737	267737	267737	113881	113881
N Labs	11399	11399	11399	10473	10473
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	85.51	1.17	0.43	4.20	200.44

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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	UG Low	UG High	Bio.	Phys. & Eng.	Psy.	NIH	NSF	<2	>2
ΔQ	-0.007	-0.170***	-0.116**	-0.022	-0.085**	-0.133***	-0.093	-0.128**	-0.083***
	(0.085)	(0.059)	(0.050)	(0.044)	(0.043)	(0.051)	(0.058)	(0.061)	(0.031)
ϵ	-0.082	-2.167***	-1.343**	-0.279	-1.038**	-1.546***	-1.221	-1.680**	-0.932***
	(1.000)	(0.749)	(0.582)	(0.551)	(0.522)	(0.590)	(0.756)	(0.803)	(0.351)
N	121246	86417	152440	42203	158975	143082	72521	125936	117105
N Labs	5285	4092	6635	1457	7691	6376	3651	9825	7659
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	0.60
Dep. Mean	49.43	163.57	87.25	80.15	89.24	87.48	98.21	82.38	106.60

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 (3) 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) Emp. Days Grad Poisson	(2) Emps. Grad Poisson	(3) Emp. Days Grad Poisson	(4) Emps. Grad Poisson	(5) Emp. Days Grad Poisson	(6) Emps. Grad Poisson
ΔQ	0.075**	0.062	0.093	0.038	0.094**	0.117***
	(0.032)	(0.040)	(0.080)	(0.065)	(0.040)	(0.036)
ϵ	0.865**	0.719	0.969	0.397	1.134**	1.418***
	(0.375)	(0.465)	(0.828)	(0.673)	(0.489)	(0.440)
N	231448	231534	93914	93942	137530	137588
N Labs	9563	9568	4729	4731	4834	4837
Lab FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.62	0.39	0.61	0.38	0.62	0.40
Dep. Mean	174.80	2.12	182.59	2.27	169.48	2.03

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

	Last Qtr FE			Time Trends		
	(1) Emp. Days Poisson	(2) Emps. Poisson	(3) Employ OLS	(4) Emp. Days Poisson	(5) Emps. Poisson	(6) Employ OLS
ΔQ	-0.102***	-0.070*	-0.024**	-0.091**	-0.066*	-0.030**
	(0.039)	(0.036)	(0.012)	(0.044)	(0.036)	(0.013)
ϵ	-1.236***	-0.846*	-0.295**	-1.104**	-0.805*	-0.361**
	(0.468)	(0.437)	(0.146)	(0.531)	(0.441)	(0.152)
N	267737	267737	267737	267737	267737	267737
N Labs	11399	11399	11399	11399	11399	11399
Lab FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Inst Linear Trends	No	No	No	Yes	Yes	Yes
Inst Quadradic Trends	No	No	No	Yes	Yes	Yes
R2	0.54	0.39	0.32	0.54	0.39	0.33
Dep. Mean	85.51	1.17	0.43	85.51	1.17	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 time trends.

Table 6. Effect of Minimum Wage Changes on Undergraduate Employment Using de Chaisemartin and D'Haultfœuille (2020) Procedure

	(1) IHS(Days)	(2) IHS(Emps)	(3) Employs
$t = 5$	-0.965	-0.223	-0.194
	(0.723)	(0.153)	(0.184)
$t = 4$	-0.718	-0.156	-0.128
	(0.745)	(0.131)	(0.152)
$t = 3$	-0.338	-0.086	-0.057
	(0.476)	(0.079)	(0.095)
$t = 2$	-0.323	-0.077	-0.054
	(0.243)	(0.060)	(0.041)
$t = 1$	-0.519*	-0.135*	-0.088
	(0.301)	(0.082)	(0.090)
$t = 0$	-0.243*	-0.070**	-0.039
	(0.135)	(0.034)	(0.028)
$t = -1$	0.009	0.012	-0.002
	(0.166)	(0.041)	(0.034)
$t = -2$	0.211*	0.075***	0.034
	(0.127)	(0.028)	(0.024)
$t = -3$	-0.226	-0.080	-0.043
	(0.234)	(0.078)	(0.042)
$t = -4$	-0.648	-0.128	-0.115
	(0.493)	(0.097)	(0.098)

Standard errors in parentheses

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

Note: The above table displays the estimated coefficients from estimating the de Chaisemartin and D'Haultfœuille (2020) procedure on observations from the Lab Panel. In Column (1), we use the dependent variable of the IHS transformed number of days of undergrad work. In Column (1), we use the dependent variable of the IHS transformed number of undergraduates working in the lab. In Column (3), we use the dependent variable of an indicator for the lab employing at least one undergraduate.

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***	-0.059**	-0.021**	-0.092**	-0.071*	-0.035**
	(0.022)	(0.029)	(0.010)	(0.036)	(0.041)	(0.014)
ϵ	-1.169***	-0.749**	-0.261**	-1.116**	-0.861*	-0.423**
	(0.273)	(0.361)	(0.128)	(0.439)	(0.500)	(0.170)
N	184966	184966	184966	72427	72427	72427
N Labs	17851	17851	17851	7466	7466	7466
Lab FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Inst Linear Trends	No	No	No	No	No	No
Inst Quadradic Trends	No	No	No	No	No	No
R2	0.56	0.37	0.35	0.58	0.38	0.37
Dep. Mean	70.40	1.00	0.48	76.12	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	0.030	0.100
	(0.035)	(0.063)	(0.086)
ϵ	0.128	0.382	1.281
	(0.465)	(0.814)	(1.102)
N	28800	50497	24006
N Labs	3663	6862	3298
Lab FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Inst Linear Trends	No	No	No
Inst Quadradic Trends	No	No	No
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	-0.002	-0.009	0.017	0.001	-0.093	0.004	0.005^{***}
	(0.012)	(0.021)	(0.019)	(0.001)	(0.124)	(0.057)	(0.001)
ϵ	-0.024	-0.107	0.205	0.014	-1.125	0.048	0.053^{***}
	(0.151)	(0.256)	(0.226)	(0.008)	(1.500)	(0.695)	(0.014)
N	267737	267737	264412	267737	144858	141222	145048
N Labs	11399	11399	11392	11399	5483	5338	6562
Lab FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.21	0.51	0.49	0.48	0.59	0.31	0.47
Dep. Mean	2.47	10.98	10.75	0.02	27,572.06	3.77	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 Possion. 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 Possion. 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
Min Wage Change	-0.027*	-0.081***	-0.015**	-0.023**	0.180*
	(0.015)	(0.012)	(0.005)	(0.008)	(0.090)
Experience		-0.063***	-0.057***	-0.057***	
		(0.014)	(0.013)	(0.013)	
Min Wage Change x Experience		0.022***			
		(0.005)			
Min Wage Change x Female			-0.003		
			(0.010)		
Min Wage Change x FWS				0.076***	
				(0.019)	
N	200168	200168	200168	200168	80589
N UGs	25021	25021	25021	25021	19706
UG FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes
R2	0.61	0.62	0.62	0.62	0.93
Dep. Mean	0.44	0.44	0.44	0.44	4.29
F-stat	3.36	76.64	63.70	35.79	4.01

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	0.008***					0.105**	0.113***
	(0.002)					(0.043)	(0.030)
MWage		-0.167**		-0.018***			
		(0.054)		(0.005)			
MWage Yr1			-0.119*		-0.031**		
			(0.060)		(0.011)		
MWage Yr2			-0.195***		-0.008		
			(0.017)		(0.006)		
MWage Yr3			-0.179*		-0.023***		
			(0.094)		(0.005)		
MWage Yr4			0.088		0.007**		
			(0.066)		(0.002)		
Constant	0.151***	1.524***	1.544***	0.170***	0.175***	0.212***	0.200***
	(0.003)	(0.026)	(0.012)	(0.003)	(0.002)	(0.066)	(0.049)
N	34,568	34,568	34,568	34,568	34,568	34,568	34,568
Inst FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.08	0.05	0.05	0.08	0.08	-0.36	-0.43
Dep. Mean	0.16	1.44	1.44	0.16	0.16	0.16	0.16
F	13.97	9.63	38.25	10.78	14.79	7,872,492.16	86,672.42

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.

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	0.002					0.025*	0.016***
	(0.002)					(0.014)	(0.005)
MWage		-0.167**		-0.004**			
		(0.054)		(0.001)			
MWage Yr1			-0.119*		-0.002		
			(0.060)		(0.001)		
MWage Yr2			-0.195***		-0.006***		
			(0.017)		(0.002)		
MWage Yr3			-0.179*		0.001		
			(0.094)		(0.001)		
MWage Yr4			0.088		0.001		
			(0.066)		(0.002)		
Constant	0.026***	1.524***	1.544***	0.032***	0.031***	-0.004	0.011
	(0.002)	(0.026)	(0.012)	(0.001)	(0.000)	(0.024)	(0.008)
N	34,568	34,568	34,568	34,568	34,568	34,568	34,568
Inst FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.02	0.05	0.05	0.02	0.02	-0.10	-0.02
Dep. Mean	0.03	1.44	1.44	0.03	0.03	0.03	0.03
F	1.86	9.63	38.25	9.78	6.53	11,769.62	2,841.25

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.

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	0.003					0.024**	0.017***
	(0.002)					(0.011)	(0.006)
MWage		-0.177***		-0.004**			
		(0.040)		(0.001)			
MWage Yr1			-0.060		-0.002		
			(0.050)		(0.001)		
MWage Yr2			-0.163***		-0.006***		
			(0.021)		(0.002)		
MWage Yr3			-0.182**		0.001		
			(0.064)		(0.001)		
MWage Yr4			0.077		0.001		
			(0.047)		(0.002)		
Constant	0.027***	0.790***	0.787***	0.032***	0.031***	0.011	0.019***
	(0.002)	(0.019)	(0.006)	(0.001)	(0.000)	(0.011)	(0.006)
N	34,568	34,568	34,568	34,568	34,568	34,568	34,568
Inst FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.02	0.03	0.03	0.02	0.02	-0.04	-0.01
Dep. Mean	0.03	0.70	0.70	0.03	0.03	0.03	0.03
F	1.72	19.96	63.48	9.78	6.53	1,704.38	257.03

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 funded by NIH on working in the life sciences.

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. We also drop universities that provide both direct expense transaction data and employee data but not 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.

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.[26] 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.[27] 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 grants that paid employees, made purchases at a vendor, and had non-negative total expenses.[28]

[26] https://github.com/benzipperer/historicalminwage/releases

[27] We exclude individuals who, for example, are paid as both "Faculty" and "Staff" or "Faculty" and "Postdoc".

[28] Negative 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

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. We also drop any labs that do not employ at least one worker at some point. 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 quarters after applying these filters.

can be created in the data.

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 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.

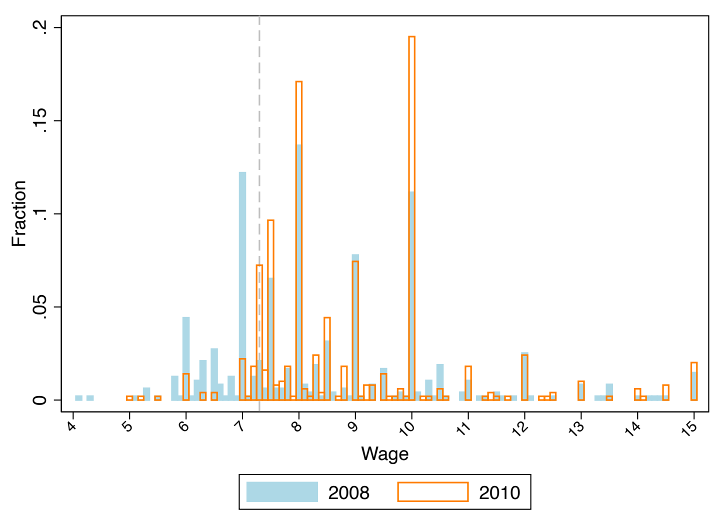
In order to make this analysis consistent with the Lab Panel Dataset, we also filter out of this dataset any individuals whose undergraduate time was at a university where we do not have complete data or cannot match employment records with vendor and direct expense data.

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 undergraudate 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 undergrad 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 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 A1, 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 A1. 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.

C 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. In addition, 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.

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.[29] 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 work performed by undergraduates that month times the wage of those employees.[30] 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

[29] We 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.

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

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.[31]

Table A1. Hedonic Regression

	Labor Pay	
	(1)	(2)
Hours	11.595	7.310
	(7.343)	(5.222)
Constant	1772.088***	1,976.347***
	(572.331)	(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.

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.[32]

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.

[31]The estimated coefficient is not statistically distinguishable using a t-test (p-value of 0.97).

[32]Note 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.

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

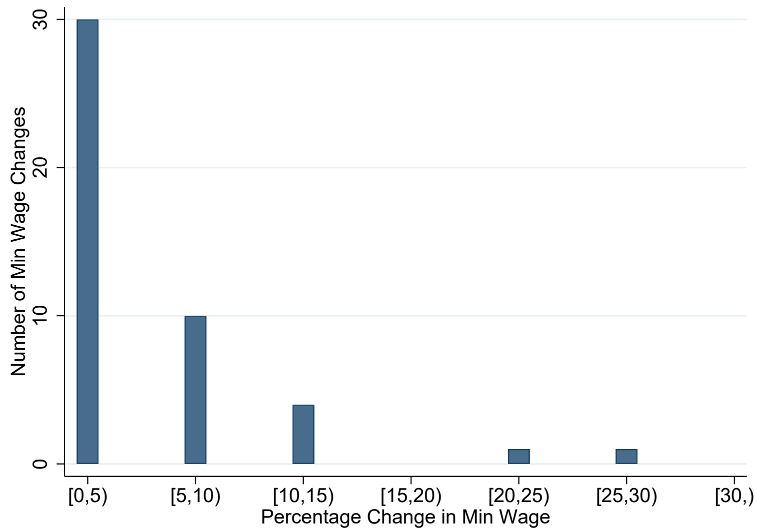
	Ln(Labor/Hours)
Ln(Mwage)	1.353***
	(0.135)
N	9,115
R2	0.67
Dep. Mean	2.74

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 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 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.

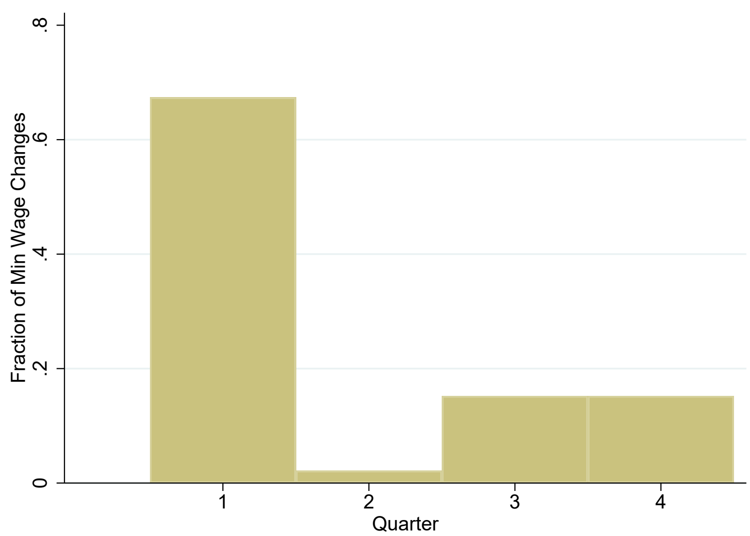
D Descriptives about Minimum Wage Changes

Figure A2. Distribution of the Magnitude of Minimum Wage Changes



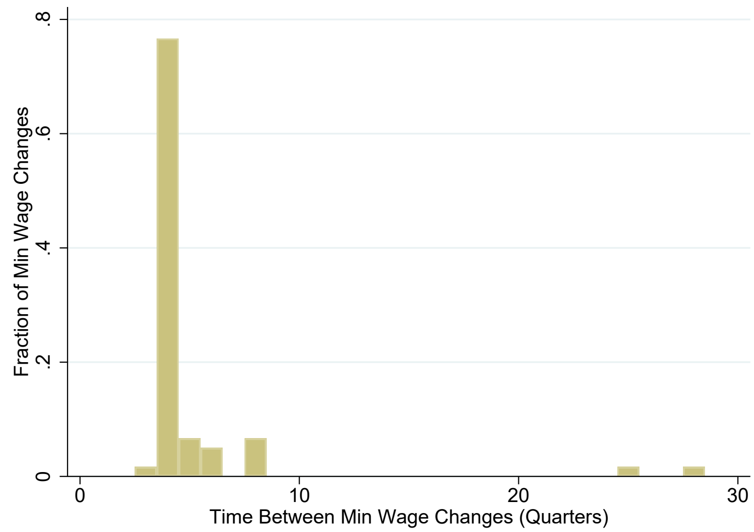
Note: The above histogram shows the distribution of minimum wage change in our sample based on the size of the minimum wage increase.

Figure A3. Distribution of the Quarter of Minimum Wage Changes



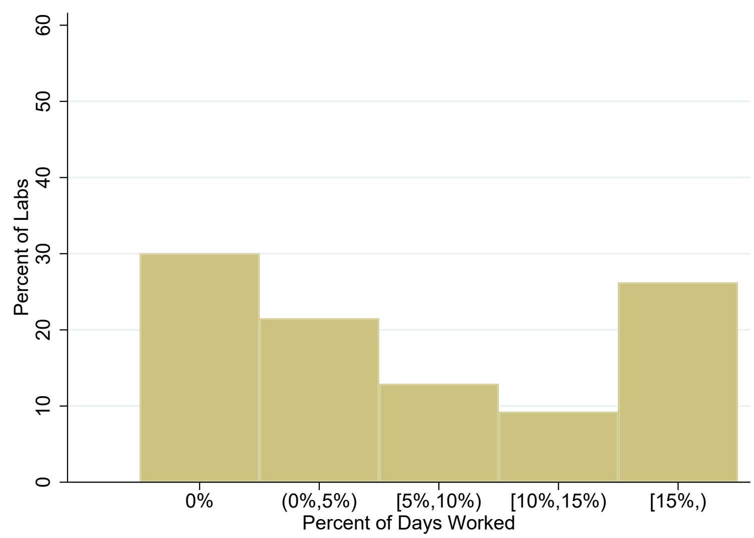
Note: The above histogram shows the distribution of minimum wage changes in our sample based on the quarter in which the minimum wage increased.

Figure A4. Distribution of Time Between Minimum Wage Changes



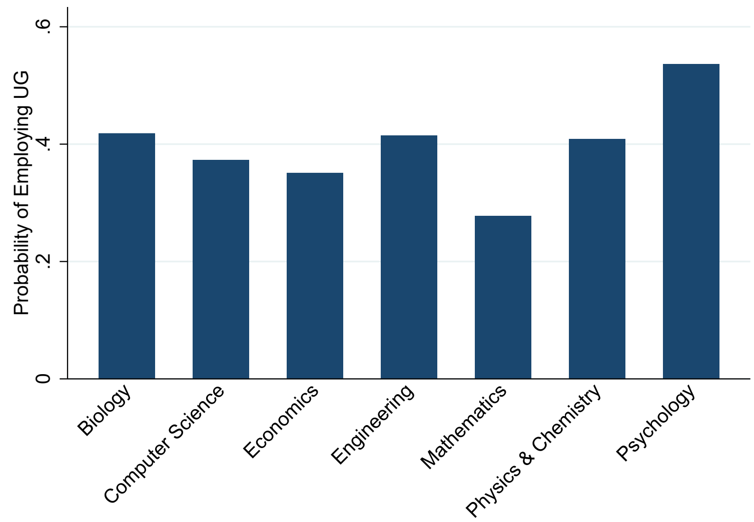
Note: The above histogram shows the distribution of minimum wage changes in our sample based on the number of quarters between changes.

Figure A5. 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 A6. 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.

E 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 A3. Balance Table of Labs Experiencing Small and Large Minimum Wage Changes

	Small Change	Large Change	*t*-stat	*p*-value
PI Female	0.22	0.21	0.48	0.63
PI Age	47.51	48.28	-3.43	0.00
Grants	2.05	2.40	-12.79	0.00
Direct Expend	92,691.04	118,186.91	-9.00	0.00
Vendor Spend	11,826.56	16,843.65	-7.11	0.00
Postdocs	0.53	0.64	-6.07	0.00
Grads	1.50	1.96	-11.09	0.00
UGs	1.02	1.27	-7.45	0.00
Staff	2.37	3.55	-12.04	0.00
N Labs	6447	4952		

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 A4. Balance Table of Labs Using Undergrads Intensively

	Not Intense	Intense	t-stat	p-value
PI Female	0.21	0.21	-0.04	0.97
PI Age	48.29	47.22	4.21	0.00
Grants	2.48	1.82	21.53	0.00
Direct Expend	127,189.12	73,930.00	16.70	0.00
Vendor Spend	17,338.98	8,999.53	10.45	0.00
Postdocs	0.70	0.38	15.47	0.00
Grads	1.79	1.49	6.56	0.00
UGs	0.64	1.99	-37.77	0.00
Staff	3.57	1.93	15.18	0.00
N Labs	5285	4092		

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

Table A5. Summary Statistics of Lab Panel Observations at Universities With and Without Graduate Student Unions

	No Union	Union	t-stat	p-value
PI Female	0.21	0.22	-2.31	0.02
PI Age	48.40	47.35	4.73	0.00
Grants	2.18	2.22	-1.47	0.14
Direct Expend	107,143.36	100,573.47	2.33	0.02
Vendor Spend	13,505.32	14,479.79	-1.39	0.16
Postdocs	0.67	0.50	9.37	0.00
Grads	1.79	1.62	4.16	0.00
UGs	0.98	1.27	-8.68	0.00
Staff	2.57	3.17	-6.16	0.00
N Labs	5541	5858		

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

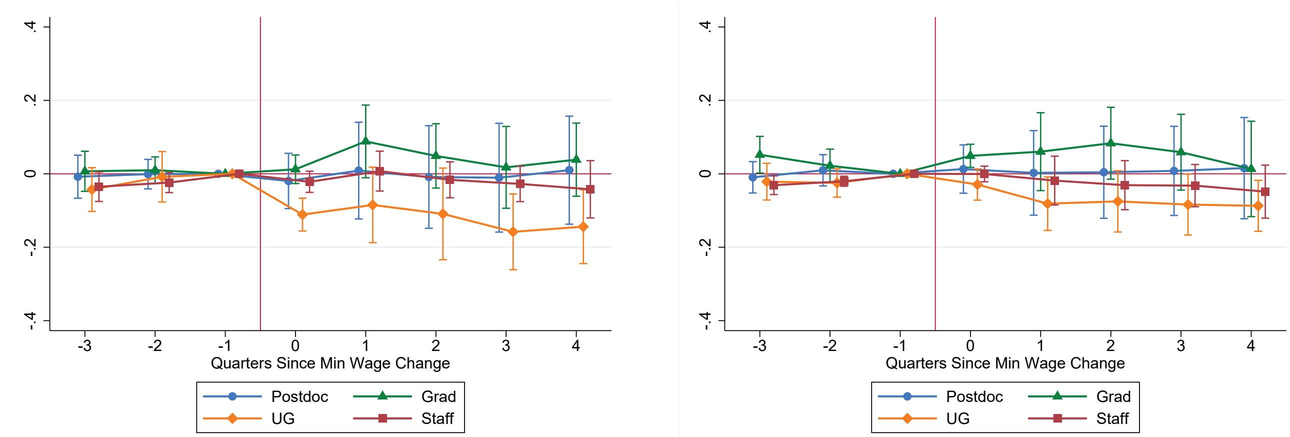
F Estimates using Indicators

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

$$E[Y_{ft}] = \sum_{j=-4}^{5} \gamma_j D^j_{ft} + \mu_f + \mu_t + \delta\Omega_{ft} + \epsilon_{ft} \tag{4}$$

In this equation, the dependent variable Y_{ft} is the outcome of interest. The independent variables include D^{j}_{ft}, 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 A7. Main Effects Using Indicators

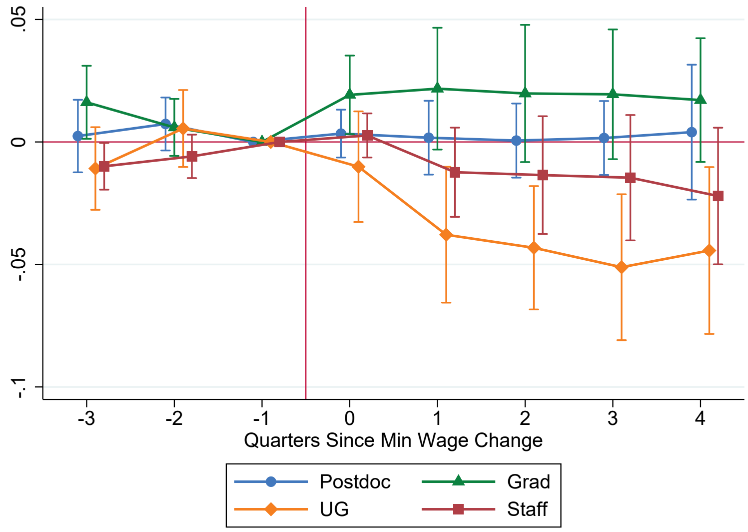


(A) Employee Days

(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 A8. 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 A6

	(1) Emp. Days Poisson	(2) Emps. Poisson	(3) Employ OLS	(4) Days/Emp OLS	(5) Intensive Poisson
ΔQ	-0.121***	-0.071**	-0.037***	-0.031	-0.051
	(0.044)	(0.032)	(0.012)	(0.021)	(0.050)
ϵ	-0.121***	-0.071**	-0.037***	-0.031	-0.051
	(0.044)	(0.032)	(0.012)	(0.021)	(0.050)
N	267737	267737	267737	113881	113881
N Labs	11399	11399	11399	10473	10473
Lab FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
Inst Linear Trends	No	No	No	No	No
Inst Quadradic Trends	No	No	No	No	No
R2	0.54	0.39	0.32	0.38	0.60
Dep. Mean	85.51	1.17	0.43	4.20	200.44

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.

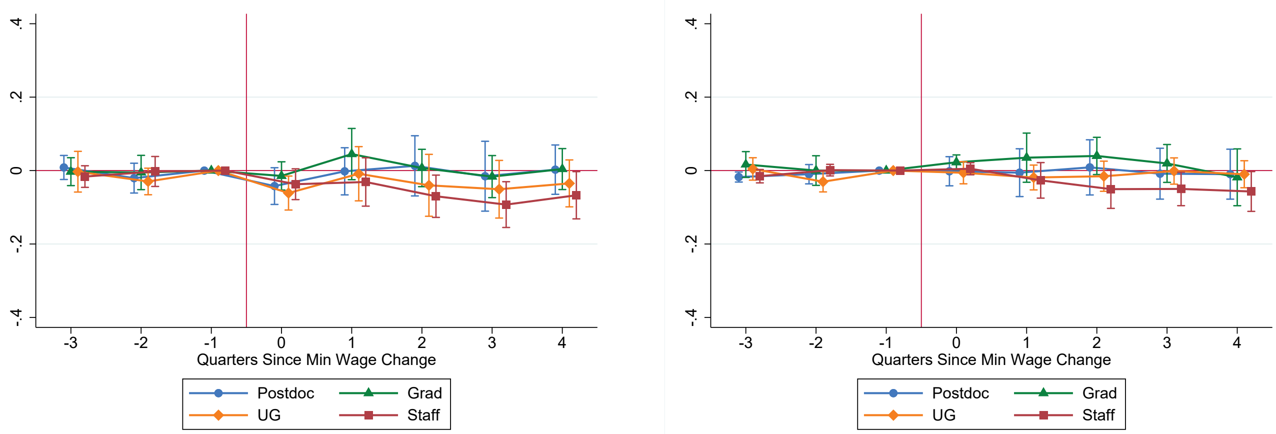
G Estimates Using Log Transformations

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:

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

Figure A9. 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 A7. University Level Estimate of Elasticities

	(1)	(2)	(3)	(4)
	Share	Ln(Emps. UG)	Ln(Days UG)	Ln(Days/Emps. UG)
Ln(MWage)	0.005*	-0.520	-1.099	-0.579
	(0.003)	(0.985)	(0.996)	(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 A8. 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	0.070	0.412**	0.114*	-0.140**	-0.222***
	(0.161)	(0.194)	(0.063)	(0.059)	(0.079)
N	267737	267737	267737	113881	113881
N Labs	11399	11399	11399	10473	10473
Lab FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
Inst Linear Trends	No	No	No	No	No
Inst Quadradic Trends	No	No	No	No	No
R2	0.54	0.39	0.32	0.37	0.60
Dep. Mean	85.51	1.17	0.43	4.20	200.44

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 A9. 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	-0.166	-0.053	0.114*	-0.140**	-0.166
	(0.095)	(0.093)	(0.063)	(0.059)	(0.095)
N	113881	115089	267737	113881	113881
N Labs	10473	10483	11399	10473	10473
Lab FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
Inst Linear Trends	No	No	No	No	No
Inst Quadradic Trends	No	No	No	No	No
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 A10

	(1) Log Emp. Days OLS	(2) Log Emps. OLS	(3) Employ OLS	(4) Log Days/Emp OLS	(5) Log Intensive OLS
ΔQ	-0.039	-0.010	-0.037***	-0.031	-0.039
	(0.027)	(0.013)	(0.012)	(0.021)	(0.027)
ϵ	-0.039	-0.010	-0.037***	-0.031	-0.039
	(0.027)	(0.013)	(0.012)	(0.021)	(0.027)
N	113881	115089	267737	113881	113881
N Labs	10473	10483	11399	10473	10473
Lab FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
Inst Linear Trends	No	No	No	No	No
Inst Quadradic Trends	No	No	No	No	No
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 A11. Effect of Minimum Wage Changes on Scientific Paper Production

	(1) WoS Publications Poisson	(2) PubMed Publications Poisson	(3) 5 Year Citations Poisson
Ln(MWage)	-0.321	0.254	-0.371
	(0.561)	(0.574)	(0.939)
N	28790	55966	24054
N Labs	11399	11399	11399
Lab FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
R2	0.75	0.64	0.79
Dep. Mean	1.19	4.50	18.47

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.

H 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 A12

	(1) Emp. Days Poisson	(2) Emps. Poisson	(3) Employ OLS	(4) Days/Emp OLS	(5) Intensive Poisson
ΔQ	-0.148***	-0.111***	-0.027*	-0.034*	-0.091
	(0.045)	(0.032)	(0.014)	(0.020)	(0.056)
ϵ	-1.755***	-1.313***	-0.324*	-0.421*	-1.121
	(0.531)	(0.374)	(0.171)	(0.251)	(0.690)
N	163039	163039	163039	65692	65692
N Labs	6140	6140	6140	5673	5673
Lab FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
Inst Linear Trends	No	No	No	No	No
Inst Quadradic Trends	No	No	No	No	No
R2	0.52	0.38	0.32	0.34	0.57
Dep. Mean	79.01	1.07	0.41	4.23	195.61

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.

I Bootstrapped Errors

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

Table A13. 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	-0.102	-0.070	-0.024	-0.015	-0.053
	(0.095)	(0.080)	(0.017)	(0.058)	(0.090)
ϵ	-1.236	-0.845	-0.295	-0.192	-0.661
	(1.145)	(0.971)	(0.208)	(0.715)	(1.122)
N	267737	267737	267737	113881	113881
N Labs	11399	11399	11399	10473	10473
Lab FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
Inst Linear Trends	No	No	No	No	No
Inst Quadradic Trends	No	No	No	No	No
R2	0.54	0.39	0.32	0.38	0.60
Dep. Mean	85.51	1.17	0.43	4.20	200.44

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.