The Effect of Funding Delays on the Research Workforce: Evidence From Tax Records*

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Abstract

Building on previous work that shows funding delays lead to a decrease in research spending, we study how the same delays affect the career outcomes of research personnel using W2 tax records that have been linked to university transaction records. Using a difference-in-differences design, employees that are part of labs with fewer grants see W2 wages decrease by 30% and the fraction of W2 wages paid by a US university decreases by 3.8 pp over a 5-year period, but the outcomes of employees that are part of labs with more grants are unchanged, suggesting that additional grants convey a protective effect. We also discuss ongoing work to better understand these results.

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"My current job started 8 years ago when my boss told me he had 6 months of guaranteed funding. I worked for him full-time for 4 years, my salary cobbled together from a half-dozen grants over that time. . . (W)hile my skills are undoubtedly valuable to a research lab, it is incredibly difficult for someone like me to find a stable job because of the funding issues and lack of recognition of the value of a supertech position." - Anonymous lab technician/manager (Guzey 2019)

1 Introduction

An important feature of US science today is the dependence of the research workforce on grants. These grants form the foundation on which academic labs are built; they support not only graduate students and postdocs – effectively serving as training grants – but allow the lab to hire other personnel such as technicians, research assistants, and research scientists. Faculty in "soft-money" positions also depend on research grants to pay at least some of their own salary.

Meanwhile, funding uncertainty is a prominent concern among scientists and policymakers, especially given the decline in federal R&D funding relative to GDP over the past decade.[1] This uncertainty comes in different forms, not all of it related to competition between labs for a limited pool of money. For example, there is yearly uncertainty over when Congress will pass a federal budget, hindering the abilities of agencies like the National Institutes of Health (NIH) and the National Science Foundation (NSF) to support both new and existing grants and plan the use of their budget.[2] There is also uncertainty over funding levels, which can fluctuate substantially from year-to-year within specific fields of science.[3]

[1]See "Federal R&D as a Percent of GDP, 1976-2020" at https://www.aaas.org/programs/r-d-budget-and-policy/historical-trends-federal-rd

[2]This is a common enough occurrence that it is explicitly discussed on the official website of the National Institute of Allergy and Infectious Diseases (NIAID), which accounted for 14% of the NIH FY2020 budget.

[3]For instance, Babina et al. (2020) use the Catalog of Federal Domestic Assistance (CFDA) to characterize research fields and find that the standard deviation in year-to-year changes in federal funding that individual researchers within a field face is 20 times the mean and 40 times the median.

We explore how the combination of grant dependence and funding uncertainty can affect the career trajectories of the scientific workforce. We focus on a particular channel, *funding interruptions*, or delays in the arrival of grant funding. Previous work has shown that when the principal investigators (PIs) of a grant experience an interruption, total PI spending decreases substantially and this decrease is largely driven by payments to employees (Tham 2021). However, Tham (2021) only observes a limited scope of employee outcomes over a short time horizon and does not observe all possible sources of support for employees (e.g. teaching positions for graduate students). Using university transaction records linked to the universe of W2 tax records, we observe career outcomes such as wages and employer characteristics over a longer time horizon, thus providing a more complete picture of the consequences of funding interruptions on research personnel. Here we focus on the following outcomes: W2 wages and the fraction of an employee's W2 wages that were paid by a US university, which proxies for the extent to which research personnel exit an academic career for a career in industry or government.

We focus on NIH "R01" grants. R01 grants are typically regarded as necessary to establish a PI's independent research lab in the biomedical sciences and expire after 4 to 5 years, at which point the PI may apply for the R01 to be renewed.[4] If a grant is successfully renewed, two scenarios are possible: (a) The grant's new funding stream begins as soon as its previous one ends (i.e. "continuous" or "uninterrupted" funding) or (b) the grant is delayed and its new funding stream only begins some time after its previous one ends (i.e. "interrupted" funding).[5]

Our research question is: how are the careers of research personnel affected by funding interruptions? We use a difference-in-differences research design that compares the outcomes of research personnel supported by PIs of interrupted R01s with the outcomes of research personnel supported by PIs with uninterrupted R01s. We define an R01 as interrupted if the time between expiry and renewal is longer than 30 calendar days, which is chosen to

[4]For every PI of an R01, we refer to the people paid by any of the PI's NIH grants as being part of their "lab".

[5]It is also possible that a grant is not renewed. Our sample of interest is R01s that are eventually renewed.

approximate a month.[6] We use a stacked regression estimator (Cengiz et al. 2019; Baker, Larcker, and Wang 2021), which avoids issues recently raised about using the two-way fixed effects estimator in a staggered difference-in-differences design (Goodman-Bacon 2018; Callaway and Sant'Anna 2020; Abraham and Sun 2018; Borusyak and Jaravel 2017).[7]

We find that when an interrupted employee was part of a lab with only one R01 at the time of interruption, they are more than 4 percentage points less likely to be paid by a university in the year the interruption occurred. There is a gradual recovery after this initial decrease but the effect persists: interrupted employees remain 2.5 percentage points less likely to be paid by a university four years after the interruption compared to employees in labs without interruptions. This is accompanied by a decrease in wages of about 30% in the year of interruption that persists at that magnitude and only diminishes four years later, when wages of employees in interrupted labs are still 16% lower than employees in uninterrupted labs.

In contrast to the substantial career impacts an interruption has on employees of a lab supported by a single R01, when an employee was part of an interrupted lab with multiple R01s, we do not see a decrease in the probability of being paid by a university or a decrease in wages compared to their peers. Tham (2021) shows that lab spending significantly drops for labs with a single R01, but does not decrease for labs with multiple R01s. Our findings build upon these results, suggesting that the protective effect of additional grants on lab spending extends to career outcomes.

Since our population of interest is geographically mobile and has a substantial portion of non-US citizens, one concern is that we do not observe the wages of employees who find jobs outside the US.[8] If interrupted employees are more likely than uninterrupted employees to find non-US jobs after the interruption, this will overstate the effect on total wages (i.e. W2 wages plus any other non-W2 wages, including wages earned from non-US

[6]Most funding begins on the first of the month, thus the arrival of new grant funding can be thought as occurring on a monthly basis.

[7]We will implement alternative estimators in future versions of the paper, including the estimator proposed in Callaway and Sant'Anna (2020).

[8]For example, according to the NSF Survey of Graduate Students and Postdoctorates in Science and Engineering, on average between 2005-2016, 35.3% of PhDs and 54.0% of postdocs were non-US citizens.

firms).[9] We will address this concern in future drafts, by examining the extent to which our W2 wage results differ when we split the sample into US-born and foreign-born samples.

Overall, these results suggest that funding interruptions can have meaningful effects on the research workforce both in terms of where they work and their earnings. We are already undertaking work to better understand the drivers of these results: Are postdocs, graduate students, or other research staff affected differently than faculty and, if so, how? What types of firms do employees who leave the university sector end up in? Are the effects on W2 wages larger for the foreign-born, suggesting that funding interruptions may lead to the migration of research personnel out of the US?

2 Data

We link three main sources of data to conduct our analysis: public-use ExPORTER data on NIH grants, UMETRICS data on payments made from grants to employees within a lab, and the universe of confidential W2 tax records available from the US Census Bureau.

ExPORTER. ExPORTER is publicly available data provided by the NIH.[10] The key variables in ExPorter for identifying interruptions are the *budget dates*, which indicate the time period when funding was allocated to a project, and the *application type*, which allows us to distinguish between funds that were previously allocated (e.g. the funds for the 3rd year of a 5-year grant) and funds that were allocated after an R01's renewal. We use these variables to identify when an R01 expired and was renewed, as well as calculate the time between expiry and renewal (see Data Appendix for more details).

UMETRICS. UMETRICS is housed at the Institute for Research on Innovation and Science (IRIS) at the University of Michigan and is derived from administrative human resource records from participating universities. The 2019 release of UMETRICS data contains data from 31 universities that represent about one-third of US federal research expenditures

[9] We also do not observe certain graduate student and postdoctoral fellowships that do not pay W2 income.

[10] https://exporter.nih.gov/

(IRIS 2019). For each university, we observe the universe of research grants as well as payments from those grants to vendors and employees. Crucially, the NIH grants in UMETRICS can be linked to NIH grants in ExPORTER, allowing us to identify employees that have a PI whose funding is interrupted. Moreover, we can link these UMETRICS employees to their W2 tax records, allowing us to observe various career outcomes, such as wages and employer characteristics.

W2 tax records. Confidential W2 tax records for years 2005-2018 are available to qualified researchers through agreements between the US Census Bureau and the Internal Revenue service. Each record is an employee paired with a federal tax identification number (EIN) and contains information on yearly wages paid to the employee from the EIN. Using a public-use list of EINs from the Integrated Postsecondary Education Data System (IPEDS), we can identify which employees receive wages from US universities and thus what fraction of their total yearly earnings is derived from a university. In future work, the EIN will also allow us to link these employee-EIN pairs to other confidential Census data, including the Longitudinal Business Database (LBD), which will enable us to observe employer characteristics. For instance, we will be able to characterize whether the employer is large or small, young or an incumbent, and whether it is in a high-tech industry.

3 Estimation

We use a difference-in-differences design to estimate the effect of funding interruptions on employees. We use a "stacked regression" as our estimator (Cengiz et al. 2019; Baker, Larcker, and Wang 2021), which involves two steps: (1) "stacking" the data by "event" (e.g. a state minimum wage increase) and (2) using an estimator which compares treatment and control units within the same event. (1) is a data formatting step and (2) exploits the data format to avoid the issues laid out in Goodman-Bacon (2018).[11] In our setting, an "event" is an R01 renewal with an interruption (more than 30 calendar days between expiry

[11]Goodman-Bacon (2018) points out that the standard two-way fixed effects estimator effectively uses already treated units as controls, which leads to biased estimates when treatment effects change over time. Recent estimators for staggered difference-in-differences avoid this problem by ensuring comparisons are "within event".

and renewal).[12] We define the year the event occurred as the calendar year the R01 was expiring. Finally, we define an employee as being "treated" by an event if they were part of a lab that had an interrupted R01 renewal. Employees are considered part of a lab if they are paid on *any* NIH grant by the PI of the focal R01 any time in the year previous to the focal R01's expiry.

For each interrupted renewal, we find control employees similarly. We find R01 renewals that were not interrupted (less than 30 calendar days between expiry and renewal) and define their (counterfactual) event year as the year the R01 was expiring. We then define an employee as a control if they were part of a lab (as defined above) with an uninterrupted R01 renewal in the same event year as the interrupted R01 renewal.

An employee could be associated with multiple R01 renewals and thus multiple labs with an R01 renewal in the same event year. We define whether they were interrupted or not based on the maximum time to renewal of the R01 renewals that employee was associated with. Similarly, if they were associated with multiple labs with an R01 renewal in the same event year, we assign them as having "one R01" or "multiple R01s" based on the lab with the highest number of R01s, out of the set of labs with R01 renewals.

For each event (and counterfactual event), we follow employee outcomes four years before and four years after the event year, creating a 9-year panel. We restrict the control group to "clean controls" who do not experience any interruption during the four years before and after the expiry year. This ensures that we are not comparing interrupted employees to already treated units.

Finally, we stack all the "event panels" to create an employee-event-year panel that is balanced on years relative to event year. The W2 tax records span the years 2005 to 2018 so this implies that our final sample is based on event years between 2009 and 2014 inclusive (in order to avoid censoring of any employee's outcomes).

We then estimate the following specification:

[12] Callaway and Sant'Anna (2020) call this a "group".

$$y_{itv} = \delta_{iv} + \gamma_{tv} + \sum_{k=-4}^{4} \beta_k * \mathbf{1}(k = t - t_v)\mathbf{1}(Interrupted) + \epsilon_{itv}$$

We index employees with i, calendar year with t, and events with v. y_{ivt} are outcomes (W2 wages and fraction of W2 wages paid by a US university), δ_{iv} are employee-event fixed effects, and γ_{tv} are calendar-year-event fixed effects. $t - t_v$ is years relative event, 0 being the event year. This is similar to the two-way fixed effects specification, except that the unit and year fixed effects are each interacted with an event indicator.[13]

4 Results

Figure 1 plots the raw means for our two outcome variables by treatment group (i.e. interrupted or continuous funding) and by whether the employee's PI had a single or multiple R01s at the time of interruption. Figure 1A shows the plots for *asinh* wages and Figure 1B shows the plot for the fraction of wages paid by a US university. For both outcomes and all groups, the means steadily rise, peaking near the treatment year, and then steadily decline.[14]

For both single- and multiple-R01 labs, Figure 1 also shows that the pre-treatment trends in employees' outcomes are similar for both the interrupted and continuous groups. In all cases, the pre-treatment levels are also quite close, with interrupted employees always slightly higher than continuously funded employees. For employees in multiple-R01 labs, the trends remain similar after the interruption and the means for the interrupted employees remain slightly higher than the continuously funded employees. In contrast, for employees in single-R01 labs, the interrupted employees experience a decline in both outcomes relative to continuously funded employees. Overall, Figure 1 is indicative of our eventual results: for employees in labs without the cushion of multiple R01s, funding interruptions cause a decline in both W2 wages and the fraction of W2 wages

[13]Intuitively, each event has its own unit and year fixed effects.

[14]The sample selects people who are paid by a grant in the year before the renewal year, so we expect people to be less likely to be paid both before and after this year.

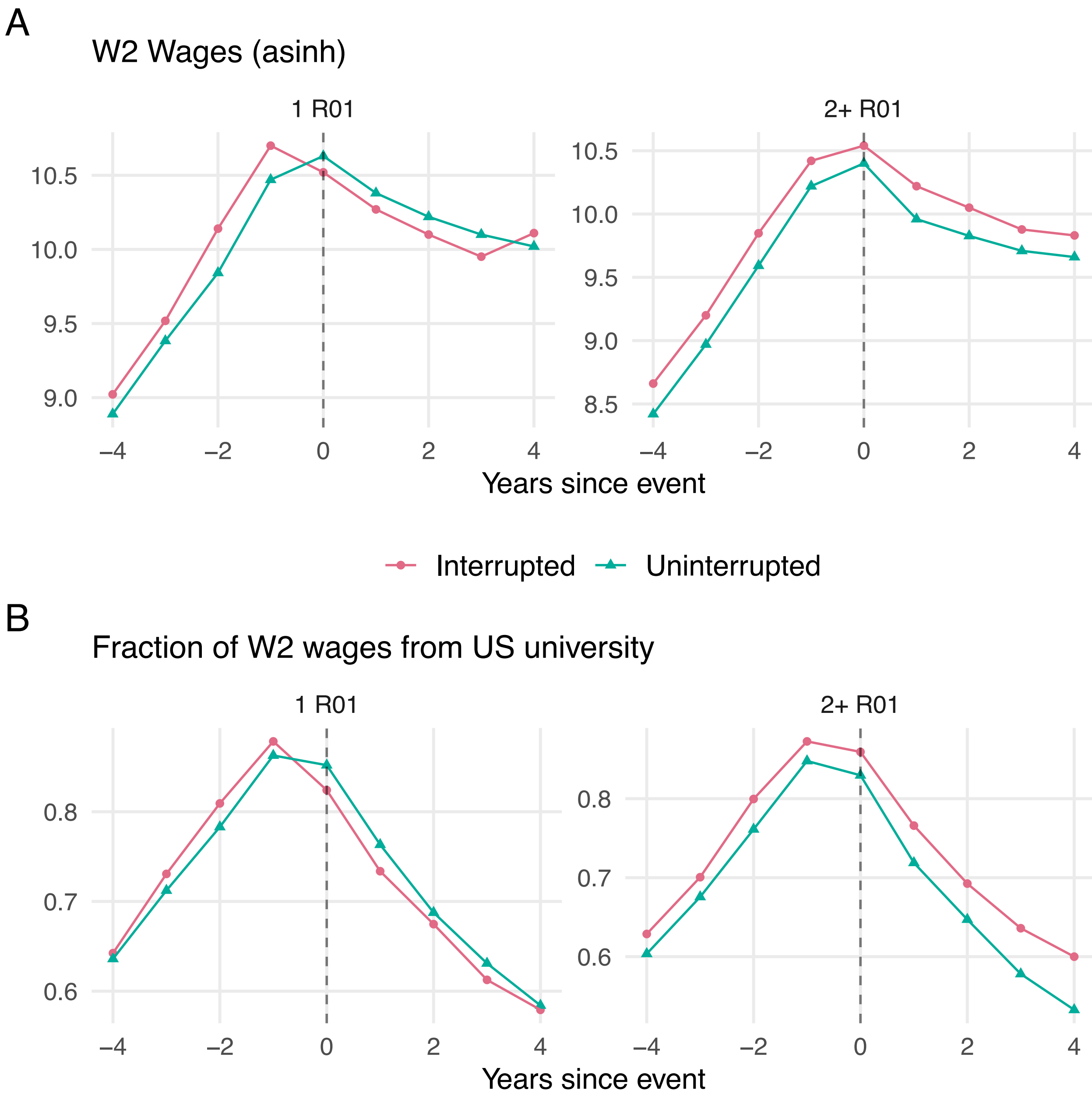

Figure 1: This figure shows the raw means every year for two outcome variables (Figure A for asinh-transformed W2 wages and Figure B for the fraction of W2 wages paid by a US university), with separate means calculated by whether the employee was part of an interrupted lab. The sample is split by the number of R01s (including R01-equivalents and P01 grants). The time period covered starts from four years before the event and ends four years after the event.

from universities.

Figure 2 plots the event study estimates. Neither outcome variable displays evidence of pre-trends, whether for employees in single- or multiple-R01 labs. As in Figure 1, interrupted employees in single-R01 labs experience a decrease in both outcomes in the year the interruption occurs. For the fraction of wages paid by a US university, there is an initial 4 percentage point decrease followed by a gradual recovery. The effect is persistent and interrupted employees remain 2.5 percentage points less likely to be paid by a university four years after the interruption. For W2 wages, there is a decrease in wages of about 30% in the year of interruption that also persists up to four years later. The magnitude of the point estimates remains at 30% except in the fourth year after interruption, where it declines to 16%.

The "static" estimates (average effect over the 5 years starting from the year of interruption) implied by the event study are a 3.8 percentage point decline in the fraction of W2 wages that come from a US university and a decrease in wages of 30%.

By contrast, interrupted employees in multiple-R01 labs experience no decline in either wages or the fraction of wages from a university, suggesting that these labs are able to use additional funding to absorb the effects of an interruption and continue supporting their employees.

Though we are able to use the universe of W2 tax records to measure wages, we do not observe the earnings of individuals paid by non-US firms or universities. This may lead to an overestimate of the effect on total wages. If, for instance, an interruption causes an employee to leave the US and work for a foreign firm, then we only observe the US portion of their wages in that year, and their earnings are recorded as a zero thereafter, even though they earn positive foreign wages. Currently, they remain in the sample because we use an arcsinh transformation of wages.

In future versions of this paper, we will probe the extent to which not observing foreign wages alters our estimates by examining the effects separately by individuals who are

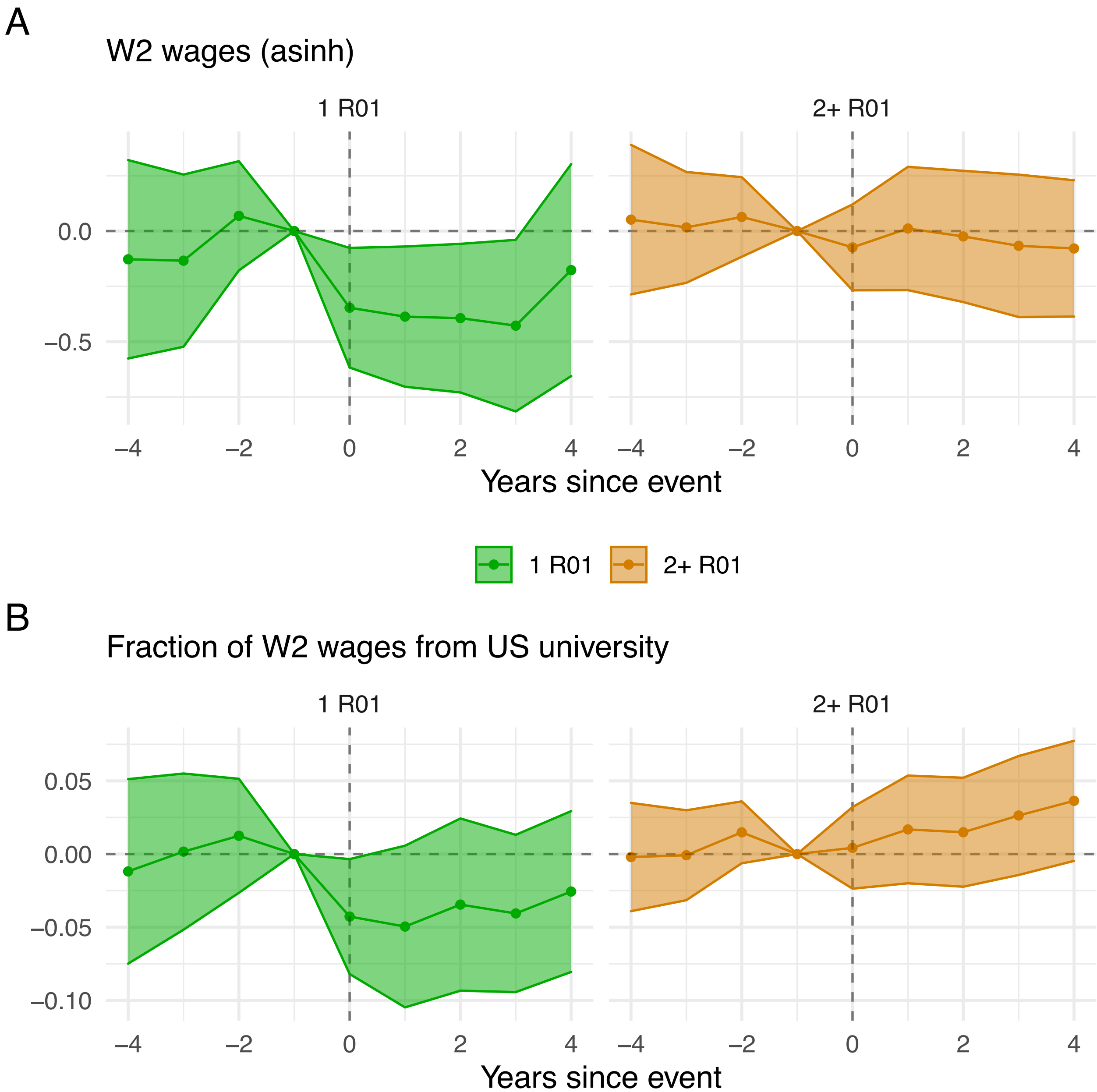

Figure 2: This figure plots the event study estimates (with 95% confidence intervals) of the difference in outcomes between employees of interrupted labs and employees of uninterrupted labs, with standard errors clustered by PI. Figure A shows the estimates for asinh-transformed W2 wages and Figure B for the fraction of W2 wages paid by a US university.

US- and foreign-born. US-born employees are more likely (due to both preferences and constraints) to remain in the US after an interruption and so W2 wages are more likely to represent their total wages. If this is the case, then the estimates for this group should more closely reflect the intensive margin effects of a funding interruption. In addition, differences in the estimates for foreign- and US-born persons will shed light on the extent to which funding interruptions may lead to the departure of research personnel from the US.

5 Conclusion and next steps

We estimate the effect of funding interruptions on the research workforce using W2 tax records. Using a difference-in-differences design, we compare the outcomes of employees whose labs had an interrupted R01 renewal (more than 30 days to renewal) and employees whose labs had an uninterrupted R01 renewal (30 days or less to renewal). We find immediate and persistent effects for employees associated with a lab with only one R01, but we also find that employees associated with a lab with multiple R01s do not experience this decrease, suggesting that better funded labs can provide more support for employees through an interruption. Our work indicates that, for a given level of funding, uncertainty about whether or when that funding will arrive appears to have material consequences for the personnel that depend on it, and reinforces the idea that *how* science funding is distributed, and not just *how much*, is substantively important.

An important dimension we will explore in future versions of the paper is how employees in different occupations are affected differently by interruptions. Understanding this heterogeneity across occupations will help to inform a variety of questions in science policy. How sensitive are the career outcomes of postdoctoral fellows to lapses in funding and what does that suggest about the potential benefits of dedicated training grants that provide predictable support for trainees?[15] What is the magnitude of earnings losses that

[15] Although training grants may not be completely protected from instability in the current system. For example, see https://drugmonkey.scientopia.org/2009/12/15/never-ever-ever-nuh-uh-no-way-ever-trust-a-dec-1-start-date/

faculty in soft-money positions face? And, returning to the quote at the beginning of the paper, what do our estimates say about the viability of a career in science for non-faculty staff such as lab technicians and staff scientists?

We will also explore in more detail where interrupted employees work after an interruption. To do this, we will link firms to the Longitudinal Business Database (LBD) using the EIN from the W2 tax records. This will allow us to characterize the type of firms at which employees work. For instance, do they work for a young firm or an incumbent? Do they work at a high-tech firm? A firm that patents? This characterization of employers will shed light on whether displaced research-trained workers flow into sectors of the economy that are suspected to be innovative and drivers of employment and productivity growth or whether they flow into more stagnant and established sectors.

Finally, we will check the robustness of our results in two ways. First, we will use an instrument that is analogous to a "judge leniency" instrument (e.g. Dahl, Kostøl, and Mogstad (2014)). Specifically, for a given R01 A, the instrument is a leave-one-out average of the time between R01 expiry and renewal of all R01s from the same NIH Institute and Center (IC) and that expired in the same month as A. Second, we will test the sensitivity of our estimates to violations of the parallel trend assumption using the methods of Rambachan and Roth (2019).

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Data Appendix

1 ExPORTER: Defining Project Periods

NIH projects are assigned a **core project number** that is used over multiple **project periods**. The funds for a project period are allocated from the NIH to the project over multiple **budget periods**.[1] Each budget period is recorded as a row in the ExPorter *Projects* data. However, ExPorter does not provide identifiers for project periods. The rest of this section explains how we construct them.

At the end of each project period, they can apply to renew funding for that project for a new project period. Thus, a project can be last for multiple project periods.

Although project periods last 4-5 years, the funds for a project are technically released over multiple *budget periods*. Each budget period is typically a year in length. ExPorter reflects this by having a new row for each time a project funds are allocated to a project. For example, project number *R01GM049850*, led by PI Jeffrey A. Simon, was funded from FY 1996 to FY 2017, except for FY 2013. Table 1 below shows the first two project periods that it was funded.

The NIH makes data on awarded grants publicly available through its ExPorter database. While projects can be identified through their R01 *core project numbers*, there is no explicit identifier for project periods. We describe below how we define project periods using ExPorter variables and data structure.

The key to defining project periods is using the *Application Type* variable.[2] This is a

[1] This is laid out in more detail in Section 5.3 of the NIH Grants Policy Statement.
[2] Detailed definitions here

Table 1: Example of NIH ExPorter data before aggregation into project periods

PI Name	Core Project Num	Fiscal Year	Application Type	Comment
Simon, Jeffrey A	R01GM049850	1996	1	New
Simon, Jeffrey A	R01GM049850	1997	5	Continuation
Simon, Jeffrey A	R01GM049850	1998	5	Continuation
Simon, Jeffrey A	R01GM049850	1999	5	Continuation
Simon, Jeffrey A	R01GM049850	2000	2	Renewed
Simon, Jeffrey A	R01GM049850	2001	5	Continuation
Simon, Jeffrey A	R01GM049850	2002	5	Continuation
Simon, Jeffrey A	R01GM049850	2003	5	Continuation

one-digit code that describes the type of "application" funded. For our purposes, the application type allows us to distinguish between what the NIH calls "competing" and "noncompeting" awards. "Competing" funds are provided as a result of having gone through a competitive process against other grant application. "Noncompeting" funds are provided as part of an already awarded project period. For the typical project, funds disbursed in the first year (i.e. just after the application process) are competing and funds awarded in subsequent years are noncompeting.

We identify R01 project periods as follows:

1. Identify all budget periods with an application type of 1, 2, or 9. These are taken to be the beginning a project period.
2. Assign a set of budget periods to the same project period if they begin in-between the beginnings of two project periods that belong to the same project.
3. Take the beginning of the budget period to be the start of the first budget period
4. Take the end of the budget period to be the end of the budget period that ends the latest. If the budget period ends after the beginning of the next project period, assign the end of the budget period to be one day before the next project period starts.

Type	Stage
1	New
2	Renewal
3	Competing Revision

4	Extension
5	Noncompeting Continuation
6	Change of Organization Status (Successor-in-Interest)
7	Change of Grantee or Training Institution
8	Change of Institute or Center
9	Change of Institute or Center