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

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Abstract

We study how an interruption in the flow of research funding from a major NIH grant — the R01 — affects the career outcomes of research personnel. Using comprehensive earnings and tax records linked to university transaction data along with a difference-in-differences design, we find that an interruption of more than 30 days has a substantial effect on job placement for personnel who work in a lab supported by a single R01, including a 2.5 pp increase in the probability of not working in the US. Half of those induced into nonemployment in the US are absent from the 2020 Decennial Census, suggesting that these personnel have permanently left the US. Among personnel who continue to work in the US, we also find that interrupted personnel earn 20% less than their continuously-funded peers. Trainees (postdocs and graduate students) experience the largest increase in the probability of no longer being in the US. Non-faculty and non-trainee personnel (such as staff and undergraduates) have the largest earnings impact.

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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

The heavy dependence of university research on federal funding is not accidental. In the aftermath of "the scientist’s war," Vannevar Bush, director of the WWII Office of Scientific Research and Development, laid out a vision for U.S. science. Bush’s 1945 report, “Science: The Endless Frontier” called for the creation of a federal science agency that would provide “stability of funds so that long-range programs may be undertaken.” The grant system that resulted, however, exhibits instabilities that harm individual scientists and ultimately science itself.

Federal funding routinely exposes researchers to grant uncertainty through, for example, the 1998–2003 boom-bust cycle of the National Institutes of Health (NIH) (Freeman and Van Reenen, 2009) and the contentious federal budgeting process with accompanying threat of government shutdown. Moreover, the process of applying for and renewing grants can itself be lengthy and unpredictable, ranging between 8 and 20 months for NIH grants, with funding often arriving long after a lab has been forced to make large cuts (Fikes, 2018; DrugMonkey, 2009, 2016; Mervis and Marshall, 1996). We examine how

\[ \text{Guided by the importance of basic research to the war effort, Bush sought to “strengthen” universities, which he viewed as essential to the production of basic research because they were “least under pressure for immediate, tangible results.” See Stephan (2013).} \]

\[ \text{The unpredictability of when a given year’s budget will be passed is such a regular occurrence that it might even be considered a permanent feature of the scientific funding landscape. For example, the National Institute of Allergy and Infectious Diseases (NIAID), which accounted for 14% of the NIH’s budget in FY 2020, explicitly addresses this issue in an online guide to the grant application process, stating that it is “assiduous about issuing awards using funds from the [continuing resolution].”} \]

\[ \text{The National Institute of Allergy and Infectious Diseases (NIAID) guide to grant timelines says that “[i]f} \]
these delays and uncertainty have affected the careers of the workforce supported by this funding, from Principal Investigators (PIs) running a lab to the personnel they hire, including trainees (e.g., graduate students, post-docs) and staff (e.g., research scientists, lab managers).

There are several challenges to quantifying the effects of funding delays on the career outcomes of lab personnel. First, in a world where delays are often caused by aggregate shocks (e.g., everyone is affected by the federal budgeting process), we must find “micro” variation in delays that affects some labs, but not others. Second, a delay implies that funding arrived late, therefore requiring a definition of when funding “should have” arrived. Third, we must link delays to the career outcomes and characteristics of lab personnel.

We address the first two challenges by focusing on a particular institutional feature of the “R01” grant, the NIH’s most common research funding mechanism. After receiving an R01 (which are usually granted for four to five years), a PI can apply to renew it for another term, and, crucially for our purposes, even successfully renewed grants can experience a delay between the expiration of the original funds and the disbursement of funds upon renewal. Using publicly available data (NIH ExPORTER), we can measure these funding delays, allowing us to identify “treated” labs that successfully renew their R01 but experience funding delays and compare them to counterfactual “control” labs that also successfully renew their grants but whose funding was not delayed, arriving when it “should have.” As a baseline, we define funding delays of more than 30 days as “interruptions.” By this definition, over 20% of grants that are successfully renewed between 2005-2018 are interrupted, with the remaining 80% being continuously-funded.

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4 Receiving an R01 is generally regarded as necessary for establishing an independent research lab in the biomedical sciences.

5 Renewal is not guaranteed – the success rate of renewal applications in a given year is about 20%.

6 Our choice of 30 calendar days is meant to approximate a month – grants are usually funded on the first of the month, so the arrival of new grant funding can be thought of as occurring on a monthly basis. We also present results separately for “short” (30 to 90 days) and “long” (90 days or more) delays, which confirm that our results are not sensitive with respect to the exact definition of an interruption.

7 Since non-renewed grants are likely to systematically differ from renewed grants, we confine our analysis
To address the third challenge, we first link successfully renewed R01s (some with funding delays, others continuously-funded) to university administrative data on grant transactions (UMETRICS database), allowing us to observe the individual personnel (e.g., faculty, postdocs, grad students, etc.) supported by these grants. We next link these grant supported personnel to their career outcomes using the universe of confidential W-2 and 1040 Schedule C tax records as well as unemployment insurance earnings records (LEHD), which provide their complete earnings and employment history in the US for 2005-2018. We also link personnel to a variety of additional data, including PubMed publications, comprehensive administrative data on demographic characteristics (age, gender, race, and ethnicity) as well as the full 2000, 2010, and 2020 Decennial Censuses, which let us examine whether grant supported personnel are present in the US even if they do not receive earnings in the US.

Using a difference-in-differences design, we compare the career outcomes of personnel in labs with an interrupted R01 to those in labs with only continuously-funded R01s. Our estimation procedure combines “stacking” by cohorts of grants set to expire in a given year (Baker et al., 2022; Cengiz et al., 2019) and the estimator from Callaway and Sant’Anna (2020). Raw means and event studies suggest that interrupted and continuously-funded personnel follow very similar career trajectories prior to grant expiration, increasing the plausibility of the parallel trends assumption underlying our analysis.

Looking only at UMETRICS data that measures the immediate inputs and outputs of science production, we found in Tham (2023) that funding delays substantially reduce grant spending, with no detectable effects on lab publication rate. By linking these funding delays to comprehensive administrative, tax, and survey data at Census, we can now examine the effects of funding delays on the career outcomes of lab personnel, including their attachment to US-science and the scientific enterprise more generally.

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8UMETRICS is maintained by the Institute for Research on Innovation and Science (IRIS) at the University of Michigan (Lane et al. 2015). The tranche of data we use includes data from 33 large US research universities (accounting for about one-third of federally funded academic R&D). See Institute for Research on Innovation and Science (IRIS) Research Support Team (2020).
We first examine how funding interruptions affect the job placements of lab personnel, the individual scientists on whom US science production relies. After an interruption, personnel in labs supported by a single R01 experience an immediate 5 percentage point (pp) decline in the probability of working at a university, which is about 53% of the baseline we would expect based on their continuously-funded peers.\footnote{Specifically, compared to the percentage point change in continuously-funded personal over same time horizon (period 0-5).} About half of these displaced single-R01 personnel find a non-university job in industry, government, or the non-profit sector, or receive income from self-employment (referred to collectively as “industry”). The other half become nonemployed in the US (i.e., they do not appear in our comprehensive tax and earnings data).\footnote{The term “nonemployed” has been used before in the economics literature (e.g., (Murphy and Topel, 1997) and Hornstein et al. (2014)) to draw a distinction from the more common term “unemployed”, which refers to people who are not working and actively looking for a job. We do not observe whether nonemployed personnel are actively looking for a job, and thus cannot observe whether they are unemployed. Furthermore, except for in the Decennial Censuses we do not observe if the individual is in the US at all.} After five years, relative to their continuously-funded peers, interrupted single-R01 personnel are as likely to work at a university and slightly less likely to work in a non-university job. However, they are permanently 2.5 pp more likely to be nonemployed in the US, which is about 31% relative to baseline. Thus, compared to continuously-funded personnel, interrupted single-R01 personnel become temporarily less likely to work at a university, temporarily more likely to work outside a university and permanently more likely to be nonemployed in the US.

In contrast to single-R01 personnel, personnel in labs supported by multiple R01s experience precisely estimated zero post-interruption changes for all employment outcomes, suggesting that PIs with alternative sources of funding can insulate their personnel from the consequences of funding interruptions. The importance of a funding cushion is widely recognized among PIs as well, with one PI we interviewed stating, “If you have only one R01 grant, then you are really exposed to the vagaries of the funding cycle.” These null effects are also consistent with evidence from Tham (2023), where we find that until the grant is renewed, interruptions lead to an almost total collapse in spending in single-R01 labs and only moderate decreases in spending for multiple-R01 labs.\footnote{See Appendix Figure A2.} We interpret this as evidence for an intuitive mechanism: interruptions constrain a PI’s funding and other
sources of funding (e.g., university-provided bridge funding) are not enough to make up for that loss, so they are unable to pay the salaries of their lab personnel. This mechanism makes it more likely that the effects we observe for interrupted single-R01 personnel are actually driven by interruptions rather than being driven by time-varying confounders that happen to affect both the likelihood of an interruption and employee outcomes.\textsuperscript{12}

The effects of interruptions on the jobs placements of single-R01 personnel are concentrated among trainees (graduate students and postdocs) and the US-born, likely reflecting differences in the stability of employment of different types of university personnel (e.g., grant vs. university supported) and visa constraints faced by the foreign-born.\textsuperscript{13} Specifically, trainees and the US-born from interrupted single-R01 labs are 6.1 and 3.5 pp more likely to enter nonemployment (be absent from the US data), and for both groups these changes are almost entirely driven by departures from universities. In contrast, we estimate precise zeros for all job placement outcomes of faculty and estimate that foreign-born personnel are half as likely as their US-born counterparts to become nonemployed (statistically insignificant 1.8 pp). Thus, long term and university supported contracts likely insulate faculty from the consequences of interruptions, while the temporary status of trainees ensures they bear the brunt. Meanwhile, the relative attachment of foreign-born personnel to university employment (and to their original university) likely reflects less flexibly in altering career plans, as visa constraints limit options if they wish to maintain their legal status in the US.\textsuperscript{14}

The seemingly permanent increase, for interrupted single-R01 personnel, in the likelihood of nonemployment in the US raises the question of what these highly-trained and highly employable\textsuperscript{15} individuals are doing. It is possible that some remain in the US, and are

\textsuperscript{12}This is a similar idea to a placebo test, although ex-ante we do not know that the effects of interruptions on the multiple-R01 sample are necessarily zero.

\textsuperscript{13}We define three occupation categories: faculty, trainees (postdocs and graduate students), and “others” (which includes occupations such as staff, research scientists, and undergrads). Although “non-US-born” is more accurate, we use the term “foreign-born” for easier reading. Some foreign-born persons could be US citizens or permanent residents, while others might be nonimmigrant visas such as the J1 or F1 visa.

\textsuperscript{14}This may also reflect differences in preferences between US- and foreign-born personnel. For example, Ganguli and Gaulé (2019) find that among Chemistry PhD students, foreign students have a stronger preference for US postdoc jobs than US citizens.

\textsuperscript{15}The Survey of Doctorate Recipients consistently finds that the unemployment rate among surveyed individuals is about 1.5%, several times lower than the overall unemployment rate.
truly not working. However, interruptions may have driven others out of the US and thus outside the scope of our US-based tax/administrative earnings data. This is an especially important consideration since the scientific workforce is relatively geographically mobile (with a full one third of our sample being foreign-born). To distinguish between those who emigrate from the US and those who are not working but still in the US, we decompose our estimates – we compute the share of the interruption-induced nonemployment increase attributable to personnel who are absent from the full 2020 Decennial Census and therefore likely to be living outside the US. We find that about half of the single-R01 personnel induced to nonemployment by an interruption are also absent from the 2020 Decennial Census, suggesting they have left the US entirely.\textsuperscript{16}

Again, the results are starkest for trainees, and, intuitively, for the foreign-born. About 70\% of trainees and nearly all foreign-born personnel induced to nonemployment by an interruption do not reside in the US by 2020. For trainees, this likely reflects the mobility of a relatively young population with less attachment to the US labor market and a greater willingness to find a job abroad. For the foreign-born, the high rate of exit from the US likely reflects visa restrictions disallowing the holder to remain in the US while not working, as well as support networks in their home countries.

Since interruptions appear to encourage the exit of scientific personnel from the US, it is natural to ask whether these personnel also leave the scientific enterprise altogether or whether they continue to produce scientific output elsewhere. Though our administrative earnings and Decennial data are comprehensive, they end at the US border, so we turn to publications to track the scientific output of personnel. We again decompose our estimates, this time computing the share of the interruption-induced nonemployment increase attributable to personnel who are publishing and thus still participating in science. We find that that vast majority – about 86\% – of single-R01 personnel who are induced to nonemployment by an interruption do not continue to publish.

Overall, our main results suggest that a particular subset of the scientific workforce – those

\textsuperscript{16}In the appendix, we also examine personnel presence in the US over time using the 2000, 2010, and 2020 Decennial Censuses, which also suggests that interruptions push single-R01 personnel out of the US.
in labs supported by a single R01 – are vulnerable to delays in the arrival of funding. Their careers are significantly impacted by an interruption as they are prematurely pushed out of universities leading to a long-term increase in the probability of becoming nonemployed in the US. Moreover, these disrupted career trajectories appear to translate into real losses for both US science and the scientific enterprise as a whole, with a large fraction of the personnel that are induced to nonemployment by an interruption leaving the US and ending their publication activities.

Though losing highly-trained research personnel may be detrimental to the scientific enterprise, it is less clear that interruptions are detrimental to the careers of individual scientists. If interruptions push personnel into higher-paying private sector jobs, which is a common narrative, their earnings could rise relative to continuously-funded peers who remain at universities. However, we find that after an interruption the earnings of single-R01 personnel decline by 23% relative to their continuously-funded peers. We view this earnings decline as prima facie evidence that interruptions not only prematurely push personnel out of universities, but also have a deleterious impact on their careers. As with job placement outcomes, the effects of interruptions on the earnings of multiple-R01 personnel are precisely estimated zeros, again suggesting that these individuals are shielded from the consequences of interruptions.

In addition to earnings, we analyze job switching behavior to assess the extent to which interruptions are detrimental to the careers of individual scientists. Higher rates of job switching indicate that interrupted personnel have less stable careers than their continuously-funded peers. We find that funding interruptions increase the likelihood of single-R01 personnel receives earning from a new university job in a year by 3.7 pp and, if anything, decrease the likelihood of switching to a new non-university job in any given year. Thus, interruptions do not push personnel into (presumably higher paying) industry jobs. Rather,

\footnote{Since our data do not include earnings outside the US, we obtain our main earnings estimates from a restricted sample that only contains personnel who are "fully attached" to the US labor market after an interruption, i.e., they are employed in the US every year post-interruption. Thus, a causal interpretation of these earnings estimates requires additional assumptions about post-treatment selection into the sample. We discuss these in further detail in the section in \textit{Wage Outcomes}. When we use the full sample of personnel, coding as zero the earnings of personnel not employed in the US, the post-interruption earnings of single-R01 personnel decline by 50% relative to their continuously-funded peers.}
personnel are pushed out of their current university job and appear to scramble to obtain new university jobs, disrupting their (often budding) academic career in the process, and explaining why they go on to earn less than their continuously-funded peers.18

A final set of results speaks to the mechanisms through which delays in the arrival of funding might impact personnel career outcomes. Interruptions are a combination of two kinds of shocks: an uncertainty shock about when funding will arrive, and a liquidity shock when funding is unavailable. We find that longer interruptions (greater than 90 days) do not seem to lead to stronger effects, suggesting that our effects are driven by the uncertainty shock for the personnel who are already working in the lab. This is partly due to how we construct the sample of interest: to be in our sample, you must be employed in a lab in the 12 months preceding an expiring R01. However, this does not mean that the liquidity shock is unimportant, since it may impact personnel who would have been hired (or would have been hired earlier) if not for the lack of funding.

As with any difference-in-differences approach, the plausibility of the estimates we lay out above hinges on a parallel trends assumption. Though untestable, there are several reasons to believe this identification assumption is plausible in our setting. First, as noted, raw means and event studies suggest that interrupted and continuously-funded personnel trend similarly prior to grant expiry. Second, though not necessary for parallel trends to hold, balance statistics suggest that interrupted and continuously-funded labs are similar across a variety of pre-expiry observables, including demographic characteristics such as gender, race, ethnicity, and place of birth. Third, as suggested, the effects of interruptions are confined to groups that, ex ante, we would expect to be most vulnerable to delays in funding – specifically, non-faculty in labs supported by a single R01. Finally, we can observe the number of resubmissions that an R01 renewal application went through before being approved, which serves as a coarse measure of (perceived) project/application quality. All of our main estimates are robust to controlling for resubmissions.

To gain further insight into the causes and consequences of funding interruptions, we

18Even in cases where people move to industry it is not clear that these jobs are as good fits as those who take industry jobs in less pressured circumstances.
interviewed six PIs who had experienced these challenges. A recurring theme in these interviews was a constant worry about the stability of funding. The PIs emphasized that labs with only one R01 were particularly vulnerable to lapses in funding. As one PI cautioned, ‘If you have only one R01 grant, then you are really exposed to the vagaries of the funding cycle.’ The PIs agreed that when funding was tight, the first area they considered cutting was personnel, leading to the departure of lab members such as technicians and postdocs. Notably, one PI recounted an instance where a technician, compelled to search for a new job due to funding uncertainty, had already moved on to a new position by the time the lab’s funding was eventually secured.

Our work lies at the intersection of two strands of literature in the economics of innovation and labor economics. In the economics of innovation, a key policy question has been whether innovators and scientists can be incentivized to do riskier or more exploratory work using funding mechanisms that are more risk tolerant (Azoulay et al., 2011; Ederer and Manso, 2013). This literature tends to focus on innovation outputs such as publications and patents. However, the importance of team-based science (Wuchty et al., 2007) means that grants not only impact the research production function of the PI (usually faculty), but also the careers of non-faculty personnel (see Baruffaldi and Gaessler (2021) for work on the role of physical capital in research production, and Babina et al. (2023) for a different view of how funding constraints can impact careers). By bringing into focus personnel beyond faculty, this paper helps to build a fuller picture of the interaction between grant funding and the research workforce.

In doing so, there are parallels between this paper and a rich literature on the impact of adverse events on the labor market (Oyer, 2006; Oreopoulos et al., 2012; Rothstein, 2021; Huckfeldt, 2022). Our work differs in that it studies a unique but important labor market, complementing work on how scientific careers can be meaningfully affected by early events (Azoulay et al., 2021; Hill, 2019). To the extent that research generates positive externalities, a better understanding of this market is important both for worker welfare as well as knowledge production, not to mention that acquiring the human capital to be part of the research workforce is individually and societally (through government investments)
costly. Another difference is that, in contrast to work that focuses on initial labor market conditions, our treatment stems from processes likely more amenable to policy solutions (i.e., it is probably easier to reduce delays in R01 funding than to avoid recessions).

Overall, we find that funding interruptions have a sizable impact on the job placements and earnings of members of the scientific workforce. After an interruption, personnel are less likely to work at a university, with half of the effect driven by individuals permanently exiting US employment and the other half driven by individuals getting new university jobs, delaying their career progression. Of the personnel who leave the administrative data, about half leave the US (absent from 2020 Decennial) and most leave science (no PubMed publications). Moreover, even personnel very strongly attached to the US labor market experience a large decline in earnings after an interruption. Most of these impacts are concentrated on non-faculty, particularly postdocs and graduate students. Thus, even though all labs in our sample are eventually funded, we find that even differences in the timing of funding can have a meaningful impact on research personnel.

The rest of the paper is organized into the following sections, which the reader can jump to by clicking on the following links: Background, Data, Estimation, Results, Conclusion.

2 Background

2.1 NIH Funding and R01 Grants

The NIH is responsible for an annual budget of $30-40 billion,\textsuperscript{19} most of which is disbursed through research grants. The R01 is the largest grant mechanism through which the NIH funds extramural research. It is designed to provide enough funding to establish an independent research career.\textsuperscript{20} An R01 project period lasts for 4-5 years, after which it must be renewed in order to receive additional funding for a subsequent project period.\textsuperscript{21} Thus, the same project can last for multiple project periods.

\textsuperscript{19}In the period this paper focuses on.
\textsuperscript{20}In interviews with NIH Principal Investigators, all of them stated that there are no or few good substitutes for getting an R01 grant.
\textsuperscript{21}They can also be shorter (1-3 years), but this is uncommon.
Principal Investigators (PIs) generally want to maintain R01 funding for as long as possible, so it is expected that as their current project period ends they will apply to renew their project for another 4-5 year project period.\textsuperscript{22} In order to avoid lapses in funding between two project periods, PIs usually start to apply for renewal about a year before a project period ends. This allows time to prepare the renewal application itself as well as time to revise and then resubmit an application that is rejected.

The focus of our paper is on the effects of temporary interruptions, so we exclusively analyze projects that are successfully renewed at least once and so span multiple project periods. Some of these grants will experience a lapse in funding between two project periods (i.e., are interrupted) and others will be funded continuously, but all will be renewed eventually. Some projects are not renewed upon expiry, and these are not used in our analysis since our focus is on differences in the \textit{timing} of funding rather than funding levels.

2.2 Where do funding interruptions come from?

Funding interruptions typically arise because, despite timely review, the NIH chooses to delay its final decision. These delays come from funder uncertainty about either (1) its budget, or (2) the quantity and quality of projects that will request funding that fiscal year, or both. In addition to uncertainty over the timing of award notice, PIs also face uncertainty over the length of the application process due to the ability to revise and resubmit unfunded grants.\textsuperscript{23}

Suppose that at the beginning of the fiscal year, the NIH knows (1) its budget and (2) its own ranking of projects available to be funded (rank could be based on project quality but also other factors such as NIH priorities). In this scenario, the NIH knows which projects it wishes to fund \textit{and} whether it can fund them before the projects are set to run out of funding. Thus, there are no funding interruptions.

\textsuperscript{22}R01 renewal is sometimes even listed as a criterion for receiving tenure (e.g., \textit{The Ohio State University College of Medicine (2020)}).

\textsuperscript{23}We can observe the number of resubmissions an application had to go through and later discuss how we incorporate this into our analysis.
Uncertainty over projects quality and quality is inherent in the review process as there are three review cycles in a fiscal year, so the NIH may hold off on funding some applications earlier in the fiscal year until it learns more about applications that arrive later in the fiscal year.\textsuperscript{24} Also, as discussed above, the NIH generally enters its first funding cycle with uncertainty over its final budget allocations. Figure 1 shows for Fiscal Years 1998 to 2018 the relationship between when the federal budget was passed that fiscal year and when the budgets of NIH grants started on average. When a grant is "In Progress" (e.g., in the third year of a 5-year grant), there is little to no relationship. But for grants that had to be competed for (i.e., "New" or "Renewed" grants), budgets tend to start later in the fiscal year if the federal budget was passed later.

Figure 1: This figure shows for Fiscal Years 1998 to 2018 the relationship between when the federal budget was passed that fiscal year and when the budgets of NIH grants started on average. Ongoing grants are in the middle years of funding. Renewed grants require new funding from the NIH.

\textsuperscript{24}In addition, external disruption can delay funding, for example, during the 1996 shutdown, paper copies of NIH peer reviews were reported to be piling up while waiting to be shipped to the next stage of review (Mervis and Marshall, 1996).
2.3 Why interruptions may affect employee outcomes

An interruption can affect a lab through the uncertainty over funding timing as well as thought the actual gap in funding. Even prior to the end of the expiring R01 delays in the renewal process create uncertainty in a PI’s future funding situation. While this may not result in an immediate need to cut expenses, personnel may leave their positions before funding officially expires due to the uncertainty over their future employment. One PI we talked to mentioned the university’s union contract requiring them to warn personnel six months out if they had not yet secured funding. Thus, this effect can occur even if a lab eventually successfully renews its R01 without an interruption.

Once there is a gap in funding, interruptions directly affect the lab by decreasing the amount of money available to spend. Since payroll comprises the bulk of most grants’ expenditures, interruptions affect the ability of a PI to continue supporting members of their lab, especially if the interrupted R01 is the lab’s only source of funding. Lab members that are on short-term contracts, such as postdocs, that may simply not have their contract renewed if funding is not readily available.

To better understand how PIs perceive and respond to the threat of interruptions, we interviewed six PIs, identified via public grant data as having had an interrupted R01. Every PI we interviewed expressed that funding lapses were a constant worry, even in non-renewal years. They stressed the importance of trying to get additional grants (preferably another R01) as a buffer against a potential lapse in funding, so that the salaries of personnel could be shifted to a different grant if necessary. As one PI put it, “if you have only one R01 grant, then you are really exposed to the vagaries of the funding cycle.”

In the event of an interruption, PIs expressed strong aversion to losing personnel as that would be the most disruptive to the functioning of the lab. However, without other grants to compensate, it is difficult to avoid cutting payroll – the largest grant expense – in the midst of a funding interruption.\textsuperscript{25} Non-graduate students are particularly vulnerable to funding interruptions.\textsuperscript{26} Several PIs expressed regret over having lost “really good

\textsuperscript{25}The only other major expense PIs brought up was animal models (e.g., mice).

\textsuperscript{26}Graduate students are thought to be less vulnerable because universities or departments have commit-
people’ due to interruptions. One PI commented that, “for me it is like surfing, we have to stay in the front of the wave, and if you get behind it quickly circles down, you don’t have people and can’t produce data.”

Thinking about the fate of those who leave, one of the PIs noted that “people who are good get picked up by other labs.” PIs also mentioned that they tried to time their hiring of people with grant funding cycles, so that postdocs and graduate students would find it natural to leave the lab around the time of a potential funding lapse. Another PI suggested that lab support staff not engaged in the publication process would be first to be let go.

Since interruptions are quite common (about 20% of the projects in our sample experience a lapse in funding exceeding 30 days), personnel and research institutions (including the NIH) are well-aware of their possibility and may have developed ways of mitigating their disruptive effects. For example, a PI’s home institution may provide bridge funding while a PI waits for delayed funding to arrive. While the PIs we interviewed acknowledged that there might be options for bridge funding, these amounts were likely to be small and unlikely to be enough to avoid losing personnel. This accords with remarks from a grants administrator (see Appendix of Tham (2023)) where we note that bridge funding was more likely to be granted for one-time purchases such as equipment rather than ongoing expenses like personnel compensation.

3 Data

We identify personnel who were part of labs that had an expiring R01 that was eventually renewed (for brevity, we sometimes refer to these R01s as simply “expiring” without qualifying that they were also renewed). We then define whether these personnel were part of an interrupted lab or a continuously-funded lab based on the length of time between expiry and renewal. Finally, we track the earnings and job placements of these personnel before and after grant expiration.

ments to fund their training (e.g., they can be shifted to teaching positions even if grant money is unavailable), although this may be less so for graduate students who are in the later stages of their program.
We link data on these three components: (1) which R01s were expiring, (2) which personnel were part of labs that depended on those R01s, and (3) the wage and job placement outcomes of those personnel. We obtain these data from: (1) ExPORTER – a public database of NIH grants, (2) UMETRICS – administrative data from universities on grant transactions, including payments to personnel, and (3) IRS/Census data including the universe of W-2 and 1040 Schedule C (1040-C) tax records and the universe of unemployment insurance (UI) wage records. Together, these data allow us to identify individuals who work in labs that potentially experienced a funding interruption and track their entire US employment and earnings history.

Figure 2: This diagram shows the process of linking R01 grants to employees and their outcomes, starting with NIH ExPORTER data at the top and ending with tax and unemployment insurance records stored at the US Census Bureau.

Figure 2 provides a graphical representation of the basic steps to accomplish this:

1. **ExPORTER** Find all instances of R01s that are successfully renewed, note the date of expiry. This returns a set of focal R01s that the rest of the data construction builds on.
2. **ExPORTER** Each focal R01 has at least one PI. For each PI, form a focal-R01-by-PI pair.
3. **ExPORTER** For each focal-R01-by-PI, find all grants administered by the PI in the 12 months prior to expiry of the focal R01.
4. **ExPORTER + UMETRICS** For each focal-R01-by-PI, find all personnel paid by any
of the grants in the previous step. These personnel constitute the PI’s “lab”.

5. **UMETRICS + Census** Merge personnel with IRS/Census earnings and employment data. Link personnel with their employers via the LEHD and W-2 data; employer characteristics come from the LEHD and the LBD, using IPEDS data.

The remainder of the section goes into more detail about these data linkages as well as variable construction. Additional detail is also available in the Data Appendix.

### 3.1 ExPORTER

ExPORTER is publicly available data provided on NIH grants provided by the NIH.²⁷ We first use ExPORTER to identify NIH grants that are eventually renewed – that is, we do not use NIH grants that expire, but are never renewed. We then use the information in ExPORTER to generate the following variables (details in Data Appendix (ExPORTER)).

**Length of funding gaps and interruptions.** This is measured as the number of calendar days between the end of a project period and the beginning of the next project period. We define an R01 as interrupted if the gap is 30 or more days, and a grant as continuously-funded if the gap is fewer than 30 days. Figure 3 shows the distribution of funding gaps for R01 renewals across all NIH grants from fiscal years 2005 to 2018. Panel A shows that about 20% of R01s were “interrupted” by our definition. Panel B shows the distribution of funding gap lengths in days (conditional on being interrupted); it is right-skewed and has a median of 88 days.

**PI grant portfolio (Number of R01s).** PIs interviewed stressed the fragility of running a lab on only one R01, and the importance of having more than one grant to smooth operations. In Tham (2023) we show that, after an interruption PIs with multiple R01s decrease spending by substantially less (in log points) than PIs with a single R01. These suggest that personnel working for PIs with multiple R01s may be less affected by funding interruptions. Thus, we compute the number of R01s to which a PI has access. We use ExPORTER PI identifiers find all NIH grants administered by a given PI in the year before,

²⁷[https://exporter.nih.gov/](https://exporter.nih.gov/)
Figure 3: This figure shows the distribution of funding gaps for renewed R01s expiring in Fiscal Years 2005 to 2018. The figure on the left, Panel A, shows the proportion of R01 grants that are interrupted using our threshold of a 30-day gap. Panel B, on the right, shows the overall distribution of funding gaps conditional on being interrupted.
the year of, and the year after expiry of the focal R01. We include R01s awarded after focal R01’s extirpation because these provide a funding cushion if they arrive promptly, and given the time lag between grant application and receiving the funds, the PI applied for these grants before the funding status of the focal R01 is known (and so they are not caused by an interruption). We define the size of the PI’s grant portfolio based on the number of “R01-equivalent” grants, including the focal R01. For brevity, we refer to this variable as the “Number of R01s” without explicitly defining the other types of grants included.

**PI lab grants.** We identify personnel who are part of a PI’s lab in the year before the expiry of the focal R01, as these are the people who are most likely to be affected by an interruption. For a given PI of an expiring R01, we identify all NIH grants administered by the PI in the 12 months prior to the focal R01’s expiry. We define all personnel paid by any of these grants during the 12 months prior to the focal-R01 expiry as part of the PI’s lab. In the next section, we discuss how we use UMETRICS to identify the individuals paid by these grants.

### 3.2 UMETRICS

UMETRICS is a database of administrative transaction-level data on payments made from university research grants to personnel and vendors. It is housed at the Institute for Research on Innovation and Science (IRIS) at the University of Michigan and is derived from university human resources records, sponsored projects, and procurement systems made available by participating universities. We use the 2020 release of UMETRICS, which contains data from 33 universities representing about one-third of US federal research expenditures (IRIS, 2019). UMETRICS universities are research-intensive – all are classified as R1 (Doctoral Universities – Very high research activity) according to the Carnegie Classification System and all rank in the top 20% of universities by federal R&D expenditures.

For each university, we observe all expenditures from research grants within the time

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28The NIH Glossary states "R01-equivalent grants are defined as activity codes DP1, DP2, DP5, R01, R37, R56, RF1, RL1, U01 and R35 from select NIGMS and NHGRI program announcements (PAs)."
period for which the data are provided, including payments from NIH R01 grants to personnel. For each of these payments, we observe the transaction date and the occupation of the individual receiving the payment. Note that occupations can change over time (e.g. a post-doc may become a faculty member).\textsuperscript{29}

Crucially, we are able to link the NIH grants in ExPORTER (see previous section) to NIH grant transactions in UMETRICS. This allows us to identify personnel that were paid by a PI whose grant is set to expire. In the next two sections, we discuss how these personnel are linked to their publication and employment outcomes.

3.3 Employment and Earnings Data

UMETRICS personnel have been linked with in Census systems to a confidential person identifier using a probabilistic matching process (Wagner et al., 2014). This identifier allows us to link UMETRICS personnel to a variety of comprehensive tax, administrative, and survey data held by the US Census Bureau.

3.3.1 IRS and Census Data

We use three sources of confidential tax/administrative data available at the US Census Bureau to derive employment and earnings outcomes. These data allow us to track the career outcomes of UMETRICS personnel both before and after their lab experiences (or does not experience) a funding interruption.

\textbf{W-2 tax records.} Form W-2 is an Internal Revenue Service (IRS) form that US employers must file listing the wages paid to an employee and taxes withheld. Each W-2 record contains an employee’s tax identification number paired with the federal tax identification number (EIN) of an employer, and information on yearly wages. EINs allow us to identify which employers are universities (see IPEDS section below).

\textbf{Longitudinal Employer-Household Dynamics (LEHD).} LEHD data contain Unemployment Insurance (UI) wage records which track earnings and employment at a quarterly

\textsuperscript{29}Personnel occupations are assigned by the UMETRICS data team using information such as job titles.
frequency. Since UI programs are administered at the state level, each record is an employee paired with the state tax identification number (SEIN) of the employer. However, the federal EIN is also available for most employee-SEIN pairs. Note that student stipends/personnel are not subject to unemployment insurance, and thus this income is not observed in the LEHD (though this income would appear on the W-2 forms).

**1040 Schedule C (1040-C) tax records.** The 1040-C tax records are available through the Integrated Longitudinal Business Database (ILBD) at the Census Bureau, and contain the population of all nonemployer firms in the United States (Goetz and Kroff, 2021; Davis et al., 2009). These 1040-C records capture earnings from self-employment.

**IPEDS.** We link the W-2 and LEHD data to a public-use list of university EINs from the Integrated Postsecondary Education Data System (IPEDS), so we can determine whether an individual is paid by a university.30 IPEDS contains EINs for most U.S.-based universities, and all UMETRICS universities are in IPEDS.

### 3.3.2 Constructing Career Outcomes

With these data, we want to understand how job placement and earnings might be affected by funding interruptions. To do so, we construct the variables below.

**Sector indicators.** We define three mutually exclusive categories to represent the sectors that an employee can belong to in a given year:

1. US university – the person received positive earnings from an IPEDS university.
2. US non-university sector – the person only received positive earnings from a non-IPEDS US employer. We also refer to this as an “industry” job.
3. Not employed in the US – the person did not receive earnings from an employer in W-2, LEHD, or ILBD data (complement of (1) and (2)).

**University placement indicators.** To understand employee movement within the university sector, we construct two additional indicators for university employment: 1. The

30The public-use list of university EINs from IPEDS can be found at https://nces.ed.gov/ipeds/datacenter/DataFiles.aspx under the title “Directory Information”. We combine the datasets from 2002 to 2018.
employee receives positive earnings from their own UMETRICS university (i.e., the university employing them at the time of R01 expiry). 2. The employee receives positive earnings from an IPEDS university other than their own.

**Wages.** We observe yearly wages for each employee from 2005 to 2018. These are derived from a combination of W-2, LEHD, and Schedule C (ILBD) wages. We define an employee’s total earnings in a given year to be their wages from self-employment (ILBD) plus whichever of either their W-2 wages or their LEHD wages is larger. That is, \( \text{wage}_{\text{total}} = \text{wage}_{\text{ilbd}} + \max\{\text{wage}_{\text{W2}}, \text{wage}_{\text{lehd}}\} \).

### 3.4 Demographic Data and the Decennial Censuses

**Demographic Data.** Demographic information for UMETRICS personnel is available from the Individual Characteristics File (ICF), which is part of the data infrastructure of the LEHD program (Vilhuber et al., 2014). Information in ICF is sourced from the Social Security Administration (SSA) Numident and the Decennial Census. The key information we are interested in is the place of birth variable, which enables us to identify whether an individual was born in the US or not.

**Decennial Census.** The Decennial Census aims to count all people residing in the US on April 1st of the Census year, regardless of nationality, immigration status, or labor force participation. Thus, being observed in the Decennial Census indicates that a person was physically present in the US at the time of the Census.\(^{32}\) These data help us distinguish between people who stop working but are still present in the US (no earnings, but present in the Census) and people who leave the US altogether (no earnings, and not present in the Census).

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\(^{31}\)The LEHD receives data from individual states unemployment insurance systems and there are two gaps that are particularly important to this study: a) Massachusetts data is not in the LEHD until 2011, and b) graduate student stipends are not covered by unemployment insurance and thus not reflected in LEHD data.

\(^{32}\)An exception are Federally Affiliated Count Overseas Operation, who are federal personnel (and their dependents) stationed outside the US (mostly military personnel). The majority (about 67%) of housing units self-responded to the 2000, 2010, and 2020 Decennial Censuses, that is, they replied to prompts to answer questions about who was living in their housing unit by mailing back a form or by phone (or in 2020 by filling out a web based form). Data is also collected from those who administer group quarters (e.g., colleges, assisted living facilities, prisons), from non-response followup operations where enumerators visit housing units, and though a number of other operations such as enumeration at transitory locations designed to count hard to count palpitations (including in 2020, use of administrative records if they were deemed high-quality after an attempt at non-response follow up).
the Census), allowing us to assess the extent to which interruptions cause members of the scientific workforce to leave the US.

### 3.5 Publication History

Our main outcomes measure the earnings and employment of lab personnel, but these stop at the US border. Publications offer a measure of an individual’s scientific activity that we can track no matter where they are employed. We use an IRIS-provided link between publications in PubMed – a bibliographic database for biomedical research produced by the US National Library of Medicine (NLM) – and personnel in UMETRICS. The link is built by first disambiguating author names in PubMed and then linking the disambiguated authors to UMETRICS personnel by name, affiliation, ORCID (where available and necessary), email address, and collaborator names.\(^{33}\)

### 3.6 Analysis Sample

Our final sample of individuals used in the analysis consists of about 4,200 unique individuals belonging to single-R01 labs and about 13,500 unique individuals belonging to multiple-R01 labs. Table 1 shows the breakdown of the individuals belonging to single-R01 labs by occupation and then by birthplace.\(^{34}\) About 21% of lab personnel are faculty, 31% are postdocs or graduate students, and the remaining 48% are individuals with other occupations such as staff and undergraduate students. About two-thirds of lab personnel were born in the US, with the remaining third born elsewhere.

\(^{33}\)We have also run our analyses using an alternative match to PubMed created by Enrico Berkes and used in Sattari et al. (2022).

\(^{34}\)The summation across categories may not always equal the total because of rounding.
Table 1: Unique Individuals in Single-R01 Labs by Occupation Category and Birthplace

<table>
<thead>
<tr>
<th>Subsample</th>
<th>N</th>
<th>Category Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Faculty</td>
<td>900</td>
<td>Occupation</td>
</tr>
<tr>
<td>Postdoc/Grad students</td>
<td>1300</td>
<td>Occupation</td>
</tr>
<tr>
<td>Others</td>
<td>2000</td>
<td>Occupation</td>
</tr>
<tr>
<td>US-born</td>
<td>2700</td>
<td>Birthplace</td>
</tr>
<tr>
<td>Foreign-born</td>
<td>1400</td>
<td>Birthplace</td>
</tr>
</tbody>
</table>

Note: Occupation is measured at the time of interruption.

4 Estimation

4.1 Stacked Difference-in-differences

We use a difference-in-differences (DiD) design to estimate the effect of funding interruptions on personnel. Our strategy involves two steps:

1. “Stack” the data by event (i.e., The focal R01’s expiration year).
2. Estimate average treatment effects (ATTs) and event studies using a modified version of the Callaway and Sant’Anna (2020) estimator (“CS estimator”) that compares interrupted and continuously-funded units within the same R01 expiry year.

Step (1) is a data formatting step that takes advantage of the fact that, in our setting, we know the R01 expiration year for not only the interrupted (treated) but also the continuously-funded (control) units. It also allows us to make explicit choices about which control units to use for each cohort of treated units. We opt to retain only “clean” controls, people that did not themselves experience an interruption during a two-year window around the expiration year. Step (2) is the application of the CS estimator to the reformatted data, this, in contrast to OLS, allows for transparent and flexible aggregation of group-time treatment effects to estimate ATTs and event studies. Each step is an independent choice in the sense that one could stack the data and use a different estimator (e.g., OLS with two-way fixed effects (Baker et al., 2022; Cengiz et al., 2019) or directly apply the CS estimator on a standard unit-time panel dataset.

In a typical staggered DiD setting, the CS estimator estimates disaggregated “group-time”
treatment effects, where groups are defined by time of treatment, which can then be aggregated as desired (e.g., as a static treatment effect or by time relative to treatment for an event study). However, control units are not assigned to groups and are used as a comparison as long as they remain untreated. This is in line with many applications where it is difficult to define a counterfactual treatment time (e.g., the year in which a state might have but did not pass a minimum wage increase). In our setting, however, both interrupted and continuously-funded R01s have an expiration date. The expiration year can therefore be used as a well-defined treatment period for both treated and control personnel.

We take advantage of this feature to group treatment and control personnel with the same expiration year into cohorts. Each cohort can be thought of as a separate DiD with only one treatment period. This means that we are more likely to be comparing personnel in labs with projects and budgets that are at similar stages in their lifecycle (e.g., personnel may be less likely to leave their job at the beginning of an R01 than at the end of an R01, so using them as control units will overstate the effect of an interruption).

These R01 expiry cohorts are then “stacked” to form a unit-by-time panel dataset where units are defined by an employee-cohort pair and time is defined by years relative to treatment year. With this data structure, it is common to use a modified two-way fixed effects estimator (with unit-cohort fixed effects and time-cohort fixed effects, (Baker et al., 2022)). We instead use the CS estimator because it allows for transparent and flexible aggregation of the group-time treatment estimates and has more modeling options (including a doubly robust estimator).

Within the set of expiring R01 grants that were eventually renewed, we define R01s as either (1) “interrupted” if they were renewed after more than 30 calendar days or (2) “continuously-funded” if they were renewed in 30 calendar days or less. In turn, an employee is interrupted or treated if they were part of a lab with at least one interrupted

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35This can be thought of as exact matching on coarsened treatment time.
36CS aggregates treatment effects by group size. Two-way fixed effects implicitly uses OLS weights which is more efficient at the cost of bias (Baker et al., 2022).
37Our choice of 30 calendar days is meant to approximate a month – grants are usually funded on the first of the month, thus the arrival of new grant funding can be thought of as occurring on a monthly basis.
R01, and they are in the control group if they were part of a lab with an expiring R01 that was continuously funded, but not part of any labs with an interrupted R01 in two years before and the two years after the focal R01 expiry.

We wish to construct treatment cohorts where control units are “clean” i.e., not treated (or experiencing the effects of treatment) in the time window of interest. For example, this would not be the case if an employee is in a lab with two R01s that are expiring in consecutive years, 2001 and 2002. The first R01 is continuously-funded in 2001, but the second R01 is interrupted in 2002. Without any restrictions, this employee would be a control unit in the 2001 cohort but be treated in 2002. Thus, we require that to be included in a cohort, control units must not be treated two years before or after the expiry year of the focal R01 (e.g., in the cohort with expiration year 2001, control units must not have been treated in any year from 1999 to 2003.).

For most of our results, we estimate the effects of funding interruptions on career outcomes separately for individuals employed in labs supported by multiple R01 grants and labs supported by a single R01 grant. Multiple-R01 labs have more funds available to continue supporting their current personnel, who are thus less likely to experience career disruptions resulting from the temporary delay in the arrival of grant funding. The importance of distinguishing between multiple-R01 and single-R01 labs is echoed in interviews with PIs as well as evident in the data – we show in Tham (2023) that funding interruptions substantially reduce grant expenditures in single-R01 labs but only modestly reduces spending (in log points) in multiple-R01 labs (see Appendix Figure A2).

### 4.2 Identification

We rely on two main assumptions to identify the average treatment effect on the treated (ATT) of an interruption on the career outcomes of personnel: (1) parallel trends and (2) no anticipation.

**Parallel Trends.** The parallel trends assumption requires that the average outcome among the treated and comparison populations would have followed parallel trends in the absence
of treatment. In our context, this means that outcomes such as employment and wages for interrupted and continuously-funded personnel would have evolved in parallel if the funding interruption had not occurred.

The parallel trends assumption allows treatment to be non-random based on characteristics that affect the level of the outcome but requires that the treatment be mean independent of characteristics that affect the trend of the outcome. For instance, highly organized PIs may select into the continuously-funded control group because they are more likely to submit their paperwork on time and avoid a funding interruption. Their high level of organization may also affect employee outcomes (e.g., by ensuring that postdocs and graduate students are regularly publishing in a timely manner). However, as long as PI organizational skills affect employee outcomes in the same way both before and after the treatment, it does not violate the parallel trends assumption.

Thus, we are mainly worried about time-varying unobserved confounders. For instance, suppose that a PI selects into an interrupted lab because they are more likely to be offered another job as their grant’s expiration date nears, so the probability of a new job offer varies over time. This offer may interrupt funding as the PI sets up their new lab at their new university and may also affect the trends of the post-expiration potential outcomes of personnel working in their old lab, even if the interruption had not taken place.

Though the parallel trends assumption cannot be tested, we present balance statistics providing evidence that interrupted and continuously-funded labs are quite similar along a variety of characteristics. We also produce raw means and event studies, neither of which show evidence of diverging trends prior to grant expiration. Moreover, if time-varying unobserved confounders were driving our results (e.g., a PI starting a new job), they presumably affect multiple-R01 labs in ways that are similar to how they affect single-R01 labs. However, in contrast to single-R01 labs, we find little evidence that the employment outcomes of personnel in multiple-R01 labs are impacted by interruptions.

No or Limited Anticipation. The no anticipation assumption requires that there is no effect of the treatment prior to the treatment actually taking place, for instance if units are aware the treatment will occur and change their behavior in advance. The limited anticipation
assumption allows for anticipation if we are willing to assume that anticipation occurs at a fixed length of time before the treatment. In this case, one can redefine the treatment period to be at the point when units are aware of treatment. We do not see any differences between treated and control outcomes before treatment, suggesting that personnel and their PIs are not anticipating interruptions more than a year in advance (since our data are at a yearly frequency). However, there may still be anticipation on a shorter time scale since, as discussed above, both PIs and personnel will want to have made contingency plans before funding officially runs out.

5 Results

5.1 Sector placement

Figure 4 displays the fraction of personnel that fall into each of our three mutually exclusive employment categories from year -5 to year 5, where year 0 is the year of R01 grant expiry. Each row represents a different outcome. The left column is for personnel in single-R01 labs and the right column is for personnel in multiple-R01 labs. Each graph shows separate trends for personnel in interrupted and continuously-funded labs.

The probability of being in a US university (Figure 4A) has an inverted U-shape, starting around 65% in year -5, peaking around 90% at year 0, and declining to 60% in year 5. In contrast, trends for the other two employment outcomes are U-shaped. The probability of being in US industry starts at 15%, declines to 5% around grant expiry, then increases to over 20% five years later. Meanwhile, the probability of being nonemployed in the US starts at 20%, declines to about 5% around grant expiry, and then increases to about 15% five years later. The shapes are to some degree mechanical, driven by our sample requirement that research personnel receive payments from a grant at their UMERTICS university during the 12 months prior to expiry (see Section 3.1).

In the multiple-R01 sample, the outcomes of personnel in interrupted and continuously-funded labs are similar before and after R01 expiry in year 0. By contrast, in the single-R01 sample, the trends of the interrupted group deviate from those of the continuously-funded
group immediately in year 0.

Between years -5 to 0, interrupted single-R01 personnel are about 2.5 percentage points (pp) more likely to receive university earnings than continuously-funded personnel, but both groups flow into the university sector at similar rates (i.e., they have similar slopes), which is consistent with the parallel trends assumption needed to estimate causal effects. Between periods -1 and 0, the trends deviate with the slope for interrupted personnel turning sharply negative and the slope for continuously-funded personnel remaining flat. The outflow difference moderates between periods 0 and 1, with the slopes of interrupted and continuously-funded personnel becoming similar. Between periods 1 and 2, the slope for interrupted personnel flattens, allowing the continuously-funded to “catch up” in terms of university departures. After this, the trends return to parallel with the two groups continuing to leave universities at similar rates and the interrupted personnel about 2.8 pp more likely to receive university earnings.

Thus, after grant expiration, both groups start flowing out of the university sector, but the interrupted personnel flow out faster – that is, they appear to leave universities earlier than they otherwise would have. This is clearer using imputed counterfactual outcomes for interrupted personnel, which are displayed in Figure 5. If the continuously-funded are a valid control group, then, in the absence of the interruption, the period 0 fraction of interrupted personnel receiving positive university earnings would have stayed steady at 93% instead of dropping to 89%. Similarly, the period 1 fraction would have been 84% instead of 80%. These temporary declines suggest that interrupted personnel left the university sector earlier than they would have in the absence of the funding interruption. By period 2, the fraction of interrupted personnel receiving university earnings is exactly what it would have been if the interruption had never occurred. Thus, interruptions appear to affect the timing of university departures, and when interrupted personnel “return to baseline” around period 2, they are not returning to universities – the outflow continues. Instead, their rate of exit simply returns to where it would have been in the absence of the

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38 These counterfactual outcomes are imputed using the true outcomes of the continuously-funded personnel. Specifically, we compute the average level difference in the outcomes during the pre-period (2.5 pp) and add it to the outcomes of the continuously-funded personnel, which correspond to counterfactual outcomes for the interrupted personnel.
Figure 4: This figure shows the average probability that an individual is in one of three mutually exclusive categories (paid by a US university, paid by a US non-university, or not paid in the US) from five years before R01 grant expiration to five years after R01 grant expiration. Figures in the left column are for individuals in a single-R01 lab and the right column is for individuals in a multiple-R01 lab. Both groups are split into continuously funded labs and interrupted labs.
As interrupted single-R01 personnel temporarily flow more quickly out of the university sector, where do they go? Figure 4A shows that between periods -1 and 0 there is a 5 pp negative swing in the relative probability of single-R01 personnel receiving university earnings (from 2.9 pp more likely to 2.1 pp less likely than their continuously-funded peers). Figures 4B and 4C show that during this same period interrupted single-R01 personnel experience a 2.5 pp positive swing in both the probability of positive non-university earnings (from 2.1 pp less likely to 0.4 pp more likely) and nonemployment (from 0.8 pp less likely to 1.7 pp more likely). Thus, as interrupted single-R01 personnel make early departures from their university, half are employed in a non-university job and half become nonemployed in the US. Though the relatively faster flow of interrupted single-R01 personnel into the non-university sector is temporary (and eventually reversed), they become permanently more likely than their continuously-funded peers to be nonemployed in the US.

Overall, the raw means clearly suggest that funding interruptions to single-R01 labs substantially alter employment patterns for the personnel of those labs – especially affecting the timing of departures from universities to the non-university sector and entrance to employment. Relative to the counterfactual imputed from continuously-funded personnel, interrupted personnel become temporarily less likely to work at a university, temporarily more likely to work outside a university, and permanently more likely to be unemployed in the US, possibly due to emigration from the US (which we address in Section 5.2). In contrast, personnel in multiple-R01 labs are mostly insulated from the consequences of interruption.

Figure 6 shows the event study estimates, using the stacked difference-in-differences method described in the Estimation Section. These are consistent with the patterns we observe in the raw means from Figure 4. The right column of graphs show that, for personnel in multiple-R01 labs, interruptions have a precisely estimated zero effect on all three employment outcomes, again suggesting that multiple funding sources insulate lab

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39 Later we will examine if these personnel stay at their UMTRICS university or move to a different university.
Figure 5: This figure shows the average probability that personal from an interrupted single-R01 lab is in one of three mutually exclusive categories (paid by a US university, paid by a US non-university, or not paid in the US) from five years before R01 grant expiration to five years after R01 grant expiration. It also shows the imputed counterfactual probability, using personal of continuously-funded labs, of being in that employment categories.
Figure 6: This figure shows event studies of the effects of interruptions on employees estimated with our modified Callaway and Sant’Anna (2020) estimator. The outcomes are the probability that an individual in one of three mutually exclusive categories: paid by a US university (A), not paid in the US (B), or paid by a US non-university entity (C). The expiration of a lab’s grant takes place at year 0. The left column is for individuals in a single-R01 lab and the right column is for individuals in a multiple-R01 lab. Standard errors are bootstrapped and clustered at the expiring-R01-level. Standard errors not available for Figure C for disclosure reasons.
personnel from the consequences of an interruption.

In contrast, the left column of graphs show that the research personnel in interrupted single-R01 labs experience an immediate 5 pp drop in the probability of receiving positive university earnings relative to their continuously funded peers. This drop is 53% of the baseline decline of 9.4 pp (from 91.0% to 81.6%) experienced by continuously-funded single-R01 personnel between periods -1 and 1. Thus, single-R01 personnel are significantly more likely to leave academia after an interruption, though as noted above, between periods 1 and 2, continuously funded personal "catch up" in their university departures, such that the different between these groups is temporary. As already suggested by the raw means, about half of these interrupted personnel are employed in a non-university job and half become nonemployed in the US, as indicated by the immediate 2.5 pp increases in the relative probabilities of both non-university earnings and non-US employment. Over the longer term, as continuously-funded personal "catch up" in their exit from academia, interrupted personal are a bit less likely than their continuously-funded peers to work in industry, but are permanently more likely to be nonemployed in the US. This permanent 2.5 pp non-US employment effect is about 30.9% of the baseline 8.1 pp increase (from 4.2% to 12.3%) in the probability of nonemployment for continuously-funded personnel between period -1 to 5.

Figure 7 presents the post-treatment effects for our employment outcomes, aggregated over the entire five year post-expiry period. We again observe that the employment outcomes of multiple-R01 personnel are unaffected by interruptions. In contrast, single-R01 personnel experience a 3 percentage point increase in the probability of non-US employment after an interruption, confirming the seemingly permanent exit of these individuals from the US labor market. The catch-up visible in the raw means of Figure 4 and the event studies of Figure 6 leads to a statistically insignificant drop in the probability of positive university earnings, despite the sharp and statistically significant initial drop.
Figure 7: This figure shows aggregated estimates of the average treatment effects (ATTs) of an interruption on three mutually exclusive employment outcomes: 1) paid by a US university, 2) paid by a US non-university, or 3) not paid in the US. The effects are aggregated over the 5 years after the expiration of a lab’s grant. The left graph is for individuals in a single-R01 lab and the right graph is for individuals in a multiple-R01 lab. Standard errors are bootstrapped and clustered at the R01-renewal level.
5.2 Presence in the United States

The post-interruption increase in the probability of US nonemployment for single-R01 personnel raises the question of what these individuals are doing, since we’ve only so far been able to say what they are not doing – namely working for pay in the United States. These individuals may still be physically present in the US, or they may have left the country entirely. Since the scientific workforce is relatively mobile, leaving the US to find a research job in another country is particularly plausible. To address this, we use Decennial Censuses, which strive to enumerate every person living in the United States and thus allow us to observe the actual presence of personnel in the US, regardless of their employment status.

First, we create two indicators that take a value of one if a personnel is nonemployed in the US and is: (1) absent from the 2020 Decennial Census (zero otherwise) and (2) present in the 2020 Decennial Census (zero otherwise). The sum of estimated post-treatment effects using these two outcomes are equal, by construction, to the estimated 3 percentage point post-treatment effect when using the main nonemployment outcome. Table 2 presents our estimates for single-R01 labs; we will focus on the first three categories here, the others will be discussed in Section 5.5. After an interruption, personnel are 1.56 pp more likely to be both non-US employed and absent from the 2020 Decennial Census. They are 1.47 pp more likely to be non-US employed but present in the 2020 Decennial Census. This suggests that slightly more than half (1.56/3 = 0.52) of the personnel induced to nonemployment by an interruption leave the US permanently, and slightly less than half (1.47/3 = 0.49) either leave for a time and were back by mid-2020, or have been present in the US while not working.

Another way to examine personnel presence in the US is to look only at presence in the Decennial Censuses. In Appendix Table A2 we use three consecutive Censuses – 2000, 2010, and 2020 – to estimate the impact of an interruption on the probability of personnel being present in each Census. We find that single-R01 personnel are about 3 percentage points less likely to be observed in a Decennial Census after an interruption, suggesting that in the long run, there is, in fact, a 3 percentage point increase in the probability of
Table 2: Effect of Interruptions on Presence in the 2020 Decennial Census if Absent From Tax Data

<table>
<thead>
<tr>
<th>Subsample</th>
<th>In 2020 Census Absent From Tax Data</th>
<th>Not In 2020 Census Absent From Tax Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>0.0146 (0.0096)</td>
<td>0.0156** (0.0067)</td>
</tr>
<tr>
<td>Foreign-born</td>
<td>-0.00887 (0.0127)</td>
<td>0.0282 (0.0184)</td>
</tr>
<tr>
<td>US-born</td>
<td>0.0262** (0.0114)</td>
<td>0.0106** (0.0052)</td>
</tr>
<tr>
<td>Faculty</td>
<td>0.0061 (0.0141)</td>
<td>-0.00208 (0.0177)</td>
</tr>
<tr>
<td>Postdoc/Grad</td>
<td>0.0193 (0.0178)</td>
<td>0.0432** (0.0177)</td>
</tr>
<tr>
<td>Other</td>
<td>0.015 (0.0126)</td>
<td>0.0114 (0.0083)</td>
</tr>
</tbody>
</table>

This table shows aggregated estimates of the average treatment effects (ATTs) in our single-R01 sample of an interruption on the not being found in the administrative data, split by whether or not a person is observed in the 2020 Decennial Census. For each group, the coefficients should sum to the overall estimate of not finding people in the administrative data. The first two rows are for all people in single-R01 labs, and the ones below it are for different sub-groups of these labs. The effects are aggregated over the 5 years after the expiration of a lab’s grant. The estimates are obtained using a modified Callaway and Sant’Anna (2020) estimator. Standard errors are bootstrapped and clustered at the interrupted R01 level.
leaving the country.

Both analyses using the Decennial Censuses suggest that a large fraction of personnel displaced by an interruption end up leaving the US altogether.

5.3 Presence in Science: Publications

As interrupted single-R01 personnel depart from universities faster than their continuously-funded peers, it is natural to next ask whether these personnel not only leave the US-based scientific ecosystem, but also leave the scientific enterprise altogether. We examine this possibility using publications in the PubMed database, linked to UMERCIS personnel, which allow us to track scientific activity beyond the US border.

Figure 8: This figure shows the event study estimates for the sample of individuals in a single-R01 lab. The outcome variable is an indicator for whether the individual had a PubMed publication in a given year. These event studies are estimated with our modified Callaway-Sant’Anna (2020) estimator; standard errors are bootstrapped and clustered at the expiring-R01-level.
Figure 8 shows that, overall, interruptions do not lead to detectable differences in publishing propensity, which is consistent with findings in Tham (2023).\textsuperscript{40} However, Table 3 shows that the vast majority of interrupted single-R01 personnel that are pushed into non-US employment also stop participating in the scientific enterprise. Specifically, separating the non-US employed by whether they publish in a given year, we create two new outcomes whose coefficients sum to the estimated 3 percentage point effect for the main non-US employment outcome (this is analogous to separating the non-US employed by whether they were present in the 2020 Decennial Census in Section 5.2). This reveals that 86\% (0.02586/0.03) of personnel induced to nonemployment by an interruption do not publish. This is especially true for the foreign-born – nearly all of the foreign-born personnel pushed to non-US employment also stop publishing.\textsuperscript{41} Some US-born personnel do remain active in science while non-US employed, with about 30\% of those pushed to nonemployment also continuing to publish.\textsuperscript{42}

<table>
<thead>
<tr>
<th>Subsample</th>
<th>Publishing</th>
<th>Not Publishing</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>0.0259***</td>
<td>0.0045</td>
</tr>
<tr>
<td></td>
<td>(0.00946)</td>
<td>(0.0059)</td>
</tr>
<tr>
<td>Foreign-born</td>
<td>0.0247</td>
<td>-0.0066</td>
</tr>
<tr>
<td></td>
<td>(0.0184)</td>
<td>(0.0114)</td>
</tr>
<tr>
<td>US-born</td>
<td>0.0253***</td>
<td>0.011*</td>
</tr>
<tr>
<td></td>
<td>(0.00960)</td>
<td>(0.0059)</td>
</tr>
</tbody>
</table>

This table shows aggregated estimates of the average treatment effects (ATTs) in our single-R01 sample of an interruption on the not being found in the administrative data, split by whether or not a person is observed with a publication in MEDLINE. For each group, the coefficients should sum to the overall estimate of not finding people in the administrative data. The first two rows are for all people in single-R01 labs, and the next four split the lab into foreign- and US-born. The effects are aggregated over the 5 years after the expiration of a lab’s grant. The estimates are obtained using a modified Callaway and Sant’Anna (2020) estimator. Standard errors are bootstrapped and clustered at the interrupted R01 level.

\textsuperscript{40}There is a downward trend for Post Graduate Researchers, which though noisily estimated may be meaningful.

\textsuperscript{41}0.02472/(0.02472-0.006551)=1.36

\textsuperscript{42}0.011/(0.011+0.02525)=0.303
In Appendix Table A3, we further decompose the non-US employment effect for personnel in single-R01 labs, simultaneously separating by both presence in the 2020 Decennial Census and publishing. The coefficients from the four new variables again sum to the effect for the main nonemployment outcome. We focus on the difference between the foreign-born and US-born because of the contrast between the two groups in Tables 2 and 3. These are discussed in Section 5.5.

Taken together, the results of this section and Section 5.2 suggest that about half of single-R01 personnel who become non-US employed after an interruption leave the US and most (86%) no longer publish. Thus, not only do interruptions to single-R01 labs cause personnel to depart early from universities, but they also push them to leave the US and to stop contributing to the scientific enterprise in the form of publications.

5.4 Earnings and Job Mobility

So far, we have seen that interruptions prematurely push some single-R01 personnel out of universities, into nonemployment, out of the US, and out of science altogether. Losing highly-trained research personnel may be detrimental to the scientific enterprise (though total publications appear largely unaffected – Figure 8), but it is not clear whether these effects are also detrimental to the career trajectories of the individual research personnel themselves.

In this section, we first examine whether interruptions are detrimental to individual careers by estimating their impact on earnings. The ex ante effects on earnings are ambiguous. On one hand, if an interruption causes a hasty departure from a university, knocking off course an individual’s career progression through academia or encouraging them to take a less well fitting industry job, then earnings may decrease relative to the counterfactual of belonging to a continuously-funded lab. For instance, if a post-doc must scramble to find another job, their progression to a tenure-track faculty position may be delayed or derailed entirely, resulting in lower earnings. On the other hand, if the interruption spurs personnel to get jobs in the higher-paying private sector their earnings may be higher than what they would have received staying in academia.
We find lower post-interruption earnings, which we take as prima facie evidence that interruptions not only prematurely push personnel out of universities, but also have a deleterious impact on their careers.

In addition, we assess the career stability of personnel in the wake of an interruption by examining job switching behavior. Studies on job loss point to job mobility as an important mechanism for catching up in terms of earnings (e.g., Oreopoulos et al. (2012)). Thus, if interruptions cause higher rates of job switching, this may indicate that affected personnel have a path towards earnings recovery, but suggests a lower quality initial job match. On the other hand, this may not be the case for individuals who remain in the academic sector post-interruption. For instance, taking a postdoc position would instead entail forgone earnings (Cheng, 2021), in which case the combination of lower earnings and higher job switching may be a sign of greater career instability.

We find that interrupted personnel do indeed engage in greater job switching, but only within the university sector, suggesting a preference to remain in or switch back to this sector after an interruption. This points toward interrupted personnel having less stable employment than their continuously-funded peers.

5.4.1 Earnings

Figure 9A displays event studies, for research personnel in both multiple- and single-R01 labs, using the arcsine of total earnings as the outcome. As with employment outcomes, interruptions have no effect on the earnings of personnel in multiple-R01 labs. The results are again starkly different for personnel in single-R01 labs, who experience a very sharp post-interruption decline in earnings that reaches about 50% after 1-2 years and about 75% after 5 years. These estimates almost surely overstate the impact of interruptions on earnings because the sample includes individuals with zero earnings. However, as suggested by our analysis of nonemployment and presence in the 2020 Decennial Census (Section 5.2), many of these individuals probably earn positive earnings outside the US, which we cannot observe using our US-based administrative/tax data.

To obtain more plausible estimates of the impacts of interruptions on earnings, we identify
Figure 9: This figure shows time-varying effects (event studies) of an interruption on the arcsine of total earnings. The expiration of a lab’s grant takes place at time 0, and the estimated interruption effects range from 5 years before to 5 years after an interruption. The green series is for individuals in a single-R01 lab and the orange series is for individuals in a multiple-R01 lab. The top graph (Panel A) is for the full sample of research personnel and the bottom graph (Panel B) is for the sub-sample of research personnel that have positive earnings in all periods from one period before expiry to five years after expiry (i.e., the fully attached sub-sample). The estimates are obtained by using our modified Callaway and Sant’Anna (2020) estimator, which accounts for well defined event years in the continuously-funded control group. Standard errors are bootstrapped and clustered at the interrupted R01 level.
subsets of research personnel defined by their attachment to the US labor market. The first subset is composed of “partially-attached” personnel, defined as having positive earnings in the year before expiration (-1) and in at least one of the six years after expiration (0-5). The second subset is composed of “fully-attached” personnel, defined as having positive earnings in all years between -1 and 5 around expiry.

Estimates obtained using these conditional-on-positive-earnings samples require additional assumptions to be interpreted as causal effects. Specifically, we are concerned with differential selection altering the sample composition with respect to which personnel remain employed in the US after an interruption. Estimates using the partially attached sample may overstate the effect of interruption on earnings (in the same way as the full sample) if personnel move between employment in the US and elsewhere or they may understate the impact if an interruption induces people to withdraw from employment entirely (e.g., induces people to retire). The estimates from the fully-attached sample further removes personnel who have true temporary nonemployment spells (e.g., leaving the labor force to care for children), likely causing estimates to understate the effect.43 Overall, we suspect that the estimates from the conditional-on-positive-earnings samples bound the true effect, as the partially-attached sample may still include people who are induced to leave the US. Investigations on whether or not people who are nonemployed remain in the US, see Table 2, suggests that as many as half of people who are induced into non-US employment may remain in the US. Thus, we are likely missing many true nonemployment spells in the fully-attached sample.44

Figure 9B displays event studies for the fully attached subsample (Census disclosure avoidance considerations prevent us from displaying the event studies for the partially-attached sample). As with the full sample, the fully-attached research personnel in multiple-R01 labs are mostly unaffected by an interruption. The point estimates are precisely estimated zeros in periods 0 through 3, drifting down slightly in periods 4 and 5. The fully-attached research personnel in single-R01 labs again experience a sharp decline in

43 Another possible source of selection arises if personnel without US citizenship or permanent residency select into the sample by accepting lower-paying jobs to remain in the US, then our estimates would overstate the effect of interruption on earnings.

44 Antidotes also suggest that academics outside the US generally make lower salaries than those in the US.
earnings after an interruption, but it is much more modest than the decline experienced by the full sample. This suggests that our earnings results are not completely driven by the exit of research personnel from the US labor market (extensive margin) and that, even conditional on employment in the US, research personnel from single-R01 labs experience substantial and permanent earnings declines after a funding interruption.

Figure 10: This figure shows aggregated estimates of the average treatment effects (ATTs) of an interruption on the arcsine of total earnings. The effects are aggregated over the 5 years after the expiration of a lab’s grant. The first three rows are for individuals in a single-R01 lab and the bottom three rows are for individuals in a multiple-R01 lab. The sample labeled ‘All’ is the full sample of all research personnel, the sample labeled ‘Partly attached’ is the sub-sample that have positive earnings one year before expiration and in at least one of the five years after expiration, and the sample labeled ‘Fully attached’ is the sub-sample that have positive earnings in all periods from one period before expiry to five years after expiry. The estimates are obtained using a modified Callaway and Sant’Anna (2020) estimator. Standard errors are bootstrapped and clustered at the interrupted R01 level.

Figure 10 confirms these results, displaying the aggregate post-treatment effects, for the full sample as well as the partially- and fully-attached subsamples, broken out separately for personnel in multiple- and single-R01 labs. For all three samples, the earnings of
mutiple-R01 personnel do not change in response to an interruption. However, for the fully-attached sample, there is a nearly significant modest decline of 5.9%, which is driven by the decline in the later periods of the event study. In contrast, and consistent with the event studies, there are large and statistically significant interruption effects for single-R01 personnel, with those in the full, partially-attached, and fully-attached samples experiencing post-interruption earnings declines of 52%, 36%, and 23%. Thus, again, even conditional on positive earnings in all post-interruption time periods (i.e., the fully attached sample), we observe substantial earnings declines for research personnel in single-R01 labs that experience an interruption to funding.

Overall, we interpret the results in this section as strong evidence that, not only are interrupted single-R01 personnel prematurely pushed out of universities, but they also suffer career disruptions that lead to a long-term decline in earnings relative to their continuously-funded peers. Thus, not only are interruptions disruptive to the science taking place in the lab, they are also disruptive to the long-term careers of the personnel working in the lab.

### 5.4.2 Job Mobility

In this section, we examine whether interruptions affect not only earnings but job mobility. First, we examine the impact of interruption on single-R01 personnel being at their own UMETRICS university versus any other university. These estimates are shown in Table A1. Though noisy, the point estimates are similar in size, but in opposite directions, suggesting that single-R01 personnel are about 2 percentage points less likely to be at their UMETRICS university and 2 percentage points more likely to be working at a different university. We interpret this as suggestive evidence that interrupted single-R01 personnel are pushed out of their particular UMETRICS university (not only the university sector overall) earlier than they would have preferred.

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45The own/original university variable take on the value one if an individual receives income from their UMETRICS university Census administrative/tax data, and zero otherwise. The new university variable take on the value one if an individual receives income from a university that is not their UMETRICS university, and zero otherwise. The relationship between these two variables and the main university variable is max(original university, new university) = main university variable. That is, both the original university and new university variables can be one in the same year.
Second, we construct a variable measuring the number of new jobs an employee has in a given year. We then identify whether these jobs are at a university. Table 4 shows the difference-in-difference estimates for having a new university or a new non-university job for the fully-attached subsample in a given year. Experiencing an interruption leads personnel to be about 3.7 percentage points more likely to have a new university job in a given year. If anything, they are less likely to move into a non-university job in a given year. Thus, single-R01 personnel who experience an interruption are more likely to change jobs, but, in particular they begin to receive earnings from another university rather than from the non-university sector. This is consistent with the results above that distinguish between UMETRICS and non-UMETRICS universities, but do not support the commonly-held notion that personnel take a higher-paying private sector job after an interruption, helping explain why single-R01 personnel experience relative post-interruption earnings decreases.

Table 4: Effect of Interruptions on Job Changes

<table>
<thead>
<tr>
<th>New University</th>
<th>New Non-University</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0370**</td>
<td>-0.0218</td>
</tr>
<tr>
<td>(0.0178)</td>
<td>(0.0189)</td>
</tr>
</tbody>
</table>

This table shows aggregated estimates of the average treatment effects (ATTs) in our single-R01 sample of an interruption on the count of new university and non-university EINs that pay wages to a person in a given year. The effects are aggregated over the 5 years after the expiration of a lab’s grant. The estimates are obtained using a modified Callaway and Sant’Anna (2020) estimator. Standard errors are bootstrapped and clustered at the interrupted R01 level.

Like the results for earnings, we interpret the job mobility results of this section as evidence of disrupted careers stemming from funding interruptions. Indeed, not only do the interrupted single-R01 personnel experience lower earnings throughout their career, but it also appears that their careers are less stable.

46 More precisely, we measure the number of new federal tax identifiers (EINs) from which personnel receive earnings. We count the number of EINs from which a personnel receives earnings this year but did not receive earnings from last year.

47 This variable was constructed as a count of new jobs rather than a binary variable indicating a new job for Census disclosure reasons. Since it is a count, the percentage point interpretation is approximate.
5.5 Heterogeneity by US- vs. Foreign-born

5.5.1 Main Employment Outcomes

The scientific workforce in the US is heavily dependent on immigration. In our sample, slightly more than a third of the personnel were born outside the US (compared to 14% for the overall US population), and visa and work authorizations potentially play an important role in constraining their job choices. To better understand how these restrictions interact with funding interruptions, we split the sample into personnel born in the US (“US-born”) and born outside the US (“foreign-born”) and thus likely to be on a visa.\footnote{Some of the foreign-born could be naturalized citizens or permanent residents, which we cannot observe in our data.}

Figure 11 displays the aggregate five-year post-interruption effects for single-R01 labs, split by whether personnel are US- or foreign-born. The impact of an interruption on positive university earnings is -3.5 pp for the US-born and 1.1 pp for the foreign-born, suggesting that it is primarily US-born personnel that are induced to prematurely depart from universities (though the sample split renders both estimates statistically insignificant). For the US-born, there is a symmetric 3.5 pp increase in the probability of nonemployment and no change (0.1 pp) in the probability of working at a non-university. For the foreign-born, interruptions increase the probability of nonemployment by 1.8 pp and decrease the probability of working at a non-university by 2.9 pp (neither estimate is statistically significant).\footnote{Five years after interruption, 23% of foreign-born personnel are nonemployed, which is over double the 10% of nonemployed US-born personnel. Thus, the 3.5 pp increase in nonemployment for the US-born is even larger than then 2.9 pp increase for the foreign-born when compared to the unconditional levels of nonemployment.}

These results suggest that interrupted single-R01 US-born personnel tend to depart from universities at faster rates than their continuously-funded peers and become nonemployed – they do not appear to find new jobs in the non-university sector. In contrast, interrupted foreign-born personnel become relatively more likely to receive university earnings and become nonemployed, but less likely to receive non-university earnings. The employment patterns we observe among the foreign-born may be related may be related to visa or work restrictions that constrain the job options available to them. Specifically, visas may
Figure 11: This figure shows, separately for US-born and foreign-born research personnel, aggregated estimates of the average treatment effects (ATTs) of an interruption on three mutually exclusive employment outcomes: 1) paid by a US university, 2) paid by a US non-university, or 3) not paid in the US. The effects are aggregated over the 5 years after the expiration of a lab’s grant. All estimates are for individuals in a single-R01 lab. The estimates are obtained using a modified Callaway and Sant’Anna (2020) estimator (see Estimation section). Standard errors are bootstrapped and clustered at the interrupted R01 level.
disallow employment aside from at their university (and for those that are no longer students, disallow nonemployment inside the US), forcing the foreign-born to scramble for another job at their university.

Appendix Table A1 sheds some light on this, showing the impacts of interruption on the probability of receiving positive university earnings from a personnel’s own UMTRICS university versus another university. After an interruption single-R01 US-born personnel are 3.5 pp more likely to leave their UMTRICS university and 3.2 pp more likely to join another university. In contrast, interrupted foreign-born personnel are more likely than their continuously-funded peers to work at both their own UMTRICS university (1.8 pp) and another university (0.7 pp).

Thus, the US-born again appear notably more mobile than their foreign-born counterparts, able to more easily leave their current employment situation, moving universities, sectors, or even become nonemployed in the US. Though the choice of foreign-born to stay in academia rather than become nonemployed or enter the non-university sector is not necessarily due to constraints imposed by visa and work authorizations, overall our results suggest foreign-born personnel face significant job mobility constraints.

5.5.2 Presence in the United States and Publishing

As previously discussed, nonemployment in our context includes personnel who experience true nonemployment spells (i.e., they are in the US, but not working) as well as personnel who are no longer present in the US (and thus absent from our US-based administrative/tax data). So, it is perhaps surprising that the US-born are more likely to be driven to nonemployment than their foreign-born counterparts, who are presumably more likely to leave the US and thus become “nonemployed.” However, in this section we show that US-born personnel are much more likely than their foreign-born counterparts to remain in the US during nonemployment spells or return to the US after time abroad.

This can be seen in Table 2, which shows the impact of funding interruptions on nonemployment, separating by whether personnel were present in the 2020 Decennial Census (see Section 5.2). For the US-born personnel about 70% of those induced to non-US em-
ployment are found in the 2020 Decennial Census, meaning they remained in the US or left and were back by mid-2020, while the remaining 30% leave the US altogether. In contrast, all of the foreign-born personnel induced to non-US employment leave the U.S. This may highlight the impact of visa requirements mandating work among the foreign-born who cannot remain nonemployed in the US, or the greater support networks that those born abroad have in their home countries.

Examining personnel presence in Decennial Censuses over time (using the 2000, 2010, and 2020 Decennial Censuses), Appendix Table A2 shows that single-R01 foreign-born personnel who experience a funding interruption are, if anything, more likely to leave the US than the point estimate for nonemployment suggests. Though interrupted US-born personnel are also less likely to be present in a Decennial Census, the effect is about half the size of their point estimate for nonemployment.

As noted in Section 5.3, Table 3 shows that nearly all of the foreign-born personnel pushed to non-US employment also stop publishing. Meanwhile, some US-born personnel do remain active in science while non-US employed, with about 30% of those pushed to nonemployment also continuing to publish.

In Appendix Table A3, we further decompose the non-US employment effect for personnel in single-R01 labs, simultaneously separating by both presence in the 2020 Decennial Census and publishing. The coefficients from the four new variables again sum to the effect for the main nonemployment outcome. We focus on the difference between the foreign-born and US-born because of the contrast between the two groups in Tables 2 and 3. These patterns reflect what is seen in those two tables: Among foreign-born personnel induced to non-US employment by an interruption, nearly all are neither in the 2020 Decennial Census nor publishing. Among the US-born about 70% do not publish, and about 70% are found in the 2020 Decennial Census, these proportions are approximately

\[
\begin{align*}
50 & (0.0262 / 0.03683) = 0.7114 \\
51 & (0.01063 / 0.03683) = 0.2886 \\
52 & (0.0282 / 0.019335) = 1.458 \\
53 & 0.02472 / (0.02472 - 0.006551) = 1.36 \\
54 & 0.011 / (0.011 + 0.02525) = 0.303 \\
55 & 0.0357 / (0.0357 - 0.00977 - 0.007738 + 0.0009497) = 1.87
\end{align*}
\]
steady within the two groups. Thus, about 46% of personal stop publishing, but are still present in the 2020 Decennial Census, and about 22% are neither publishing nor present in the 2020 Decennial Census. Another 23% are both present in the 2020 Decennial Census and continue to publish, while the remaining 9% are not present in the 2020 Decennial Census but do continue to publish. Thus, the plurality of US-born personnel leave US science, but either remain in the US (perhaps officially retiring) or leave but return to the US by mid-2020.

About half of single-R01 personnel who become non-US employed after an interruption leave the US and most (86%) no longer publish. However, these patterns are especially strong for the foreign-born, nearly all of whom leave the US and stop publishing after becoming non-US employed due to an interruption. Among the US-born about 70% stop publishing, but in contrast, about 70% are present in 2020. Thus, while the impact on participation in the scientific enterprise in the form of publications may be similar, immigrant scientists are particularly likely to be induced to leave the US altogether because of a funding interruption.

5.6 Heterogeneity by Occupation

5.6.1 Employment Outcomes

Contractual arrangements vary dramatically across different types of personnel within a lab. In a typical lab, for instance, the faculty PI of a lab is on a permanent contract with the university, supported by university money, while postdocs will be on temporary contracts with no guarantee of renewal, and supported by grants funding. Graduate students have a finite horizon at the university, but likely have guarantees (implicit or explicit) that they will be employed somehow – if not in a research position, then in a teaching position – though these commitments may be weaker the closer they are to graduating and differ between universities. There is variation even among faculty contracts. In the biomedical

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50.01815/(0.008823+0.01815+0.003393+0.009127)=0.4596
57.0.008823/(0.008823+0.01815+0.003393+0.009127)=0.2234
58.0.0099127/(0.008823+0.01815+0.003393+0.009127)=0.2311
59.0.003393/(0.008823+0.01815+0.003393+0.009127)=0.8591
Figure 12: This figure shows, separately by occupation category of research personnel, aggregated estimates of the average treatment effects (ATTs) of an interruption on three mutually exclusive employment outcomes: 1) paid by a US university, 2) paid by a US non-university, or 3) not paid in the US. The effects are aggregated over the 5 years after the expiration of a lab’s grant. All estimates are for individuals in a single-R01 lab. The estimates are obtained using a modified Callaway and Sant’Anna (2020) estimator (see Estimation section). Standard errors are bootstrapped and clustered at the R01-renewal level.
sciences, faculty are often on “soft money” contracts, where some part or even all of
their salary is funded by external grants, with no guarantee of salary from the university,
even in exchange for teaching. Other faculty, particularly in medical schools, might be
asked to raise their salaries either through grants or through clinical work, that is, seeing
patients in an associated hospital. Staff, also vary in their funding support, with some
being fully grant funded and on year to year contacts, where as other have permanent
jobs with the university. Thus, it is reasonable to suspect that some occupations may be
disproportionately affected by the impacts of funding interruptions.

Figure 12 presents aggregate post-interruption effects, for single-R01 labs, broken out by
three broad occupation categories: faculty, postdoc/graduate student, and “others.”

The employment effects of interruptions fall mainly on single-R01 trainees – postdocs
and grad students. After an interruption, these trainees are 5.4 pp more likely to leave
universities relative to their continuously-funded peers and nearly all of them are pushed
into nonemployment (6.1 pp increase) rather than the non-university sector (as with the
place of birth sample split, the occupation sample split renders most estimates statistically
insignificant). In contrast, the effects on university departures for faculty and other occupa-
tions are near zero. “Other” research personnel are 2.6 pp more likely to be nonemployed
after an interruption, but faculty appear to be fully insulated with precisely estimated null
effects for the remaining employment outcomes.

Table 2 shows that for postdocs and graduate students, 70% of the nonemployment effect is
associated with being absent from the 2020 Decennial Census, indicating that interruptions
push these personnel out of the US scientific ecosystem.

In UMECTRICS, personnel are classified into one of six occupation categories: faculty, post-doc, grad
student, undergrad, other student, and staff. Census disclosure considerations prevent us from displaying
estimates for all disaggregated occupation categories.

In UMETRICS, personnel are classified into one of six occupation categories: faculty, post-doc, grad
student, undergrad, other student, and staff. Census disclosure considerations prevent us from displaying
estimates for all disaggregated occupation categories.

In contrast, nearly all faculty
and about 57% of personnel in “other” occupations that are induced to nonemployment
by an interruption are present in the 2020 Decennial Census.
5.6.2 Earnings

Figure 13 shows how interruptions differentially impact the earnings of fully-attached (see Section 5.4.1) single-R01 personnel, separated into aggregated occupation categories. Earnings decline by 5% for faculty but the estimate is statistically insignificant. In tandem with small employment effects, this suggests that interruptions are minimally disruptive to the careers of faculty. For trainees (postdocs and grad students), the earnings decline is substantially larger at 20%, though still statistically insignificant. For personnel in “other” occupations, the earnings decline is 30% and statistically significant, though the confidence intervals are quite wide. Thus, not only do non-faculty bear the brunt of the displacement effects of interruptions, they also suffer the largest long-term decline in earnings. In our PI interviews, several noted that lab staff were generally able to find jobs in other labs at the university. However, the large earnings declines experienced by non-faculty personnel in our sample suggest these new jobs may be a lower quality match.

5.7 Mechanism: Lack of Funding vs Uncertainty

The effects of interruptions on the employment and earnings of lab personnel could be driven either directly by the funding gap between R01 renewals or by the pre-expiry uncertainty about whether new R01 funding will be obtained at all (or both). We test this indirectly by examining whether the effects of interruption vary by interruption length. Because the CS estimator only accommodates binary treatments and not continuous or discrete multi-valued treatments, we create two treated samples – personnel in labs with “short” interruptions (interruptions of 30 to 90 days) and personnel in labs with “long” interruptions (interruptions of 90 days or more). We then obtain estimates for each of these treatment groups using the same control group as before but omitting the other treatment group.

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63 The choice is to either cut technicians (ancillary support) or “project leaders” and I cut the technicians because they don’t write papers or finish projects. I’ve lost some really good people who were picked up by other labs. Often we do find people who are good get picked up by other labs or biotech industry.

64 The larger estimate for “other” occupations may be partly driven by undergraduates taking lower paying jobs if they are released from a research job. However, it is likely that many undergraduate students transition to nonemployment (and are thus omitted from the fully-attached sample) and do not experience long-term earnings declines.
Figure 13: This figure shows aggregated estimates of the average treatment effects (ATTs) of an interruption on the arcsine of total wages, by estimates from splitting the data by occupation. The effects are aggregated over the 5 years after the expiration of a lab’s grant. The overall sample is individuals in a single-R01 lab and ‘Fully attached’ to the US labor force i.e., the subsample that has positive earnings in all periods from one period before expiry to five years after expiry. The estimates are obtained using a modified Callaway and Sant’Anna (2020) estimator (see Estimation section). Standard errors are bootstrapped and clustered at the R01-renewal level.
Table 5: Effect of Interruptions by Length of Interruption

<table>
<thead>
<tr>
<th>Interruption Length</th>
<th>US University</th>
<th>US Non-University</th>
<th>Not in US Data</th>
<th>asinh(Wages)</th>
</tr>
</thead>
<tbody>
<tr>
<td>30-90 days</td>
<td>-0.0192</td>
<td>-0.0259</td>
<td>0.0451***</td>
<td>-0.253***</td>
</tr>
<tr>
<td></td>
<td>(0.0232)</td>
<td>(0.0228)</td>
<td>(0.0160)</td>
<td>(0.0884)</td>
</tr>
<tr>
<td>&gt;90 days</td>
<td>-0.0234</td>
<td>0.0125</td>
<td>0.0109</td>
<td>-0.1952***</td>
</tr>
<tr>
<td></td>
<td>(0.0271)</td>
<td>(0.0169)</td>
<td>(0.0149)</td>
<td>(0.0684)</td>
</tr>
<tr>
<td>Subsample</td>
<td>All</td>
<td>All</td>
<td>All</td>
<td>Fully Attached</td>
</tr>
</tbody>
</table>

This table shows aggregated estimates of the average treatment effects (ATTs) of our main outcomes in our single-R01 sample of an interruption, split by the length of that interruption. Since the median interruption is 88 days, roughly half the interruptions are in each group. The first four rows are for those with ‘short’ interruptions, while the last four are for those labs with ‘long’ interruptions. The effects are aggregated over the 5 years after the expiration of a lab’s grant. The estimates are obtained using a modified Callaway and Sant’Anna (2020) estimator. Standard errors are bootstrapped and clustered at the interrupted R01 level.

Table 5 shows that impacts are felt in labs experiencing both short and long interruptions, suggesting that the direct lack of funding does not fully explain the disruptive effects and raising the possibility that uncertainty plays an important role in propagating the consequences of interruptions. Indeed, personnel in labs with short and long interruptions experience 1.9 and 1.3 pp decreases, relative to their continuously-funded peers, in the probability of university earnings. Moreover, among personnel who remain fully attached to US employment, earnings declines are similar for both interruption lengths – 25% and 20% for personnel in labs with short and long interruptions, respectively. However, personnel in labs with short interruptions are more likely to become nonemployed and less likely to enter the non-university sector than personnel in labs with long interruptions.

The fact that single-R01 personnel in labs with short interruptions experience similar employment and earnings effects as personnel in labs with long interruptions suggests that our main results are not fully driven by the temporary lack of funding that accompanies interruptions. Indeed, as researchers we observe that the interrupted labs in our sample eventually had their R01s renewed. However, pre-expiry, it would have been unclear to PIs whether additional funding would ever be forthcoming. Thus, it appears that this pre-expiry uncertainty over the arrival of funding may play a key role in explaining the disruptive impacts of interruptions. As we noted above, one PI we talked to mentioned...
the university’s union contract requiring them to warn personnel six months out if they had not yet secured funding. This PI said that, at least once, funding came through at the last minute but a technician had already found another job. Thus, effect of interruptions can occur even if a lab eventually successfully renews its R01 without a break in funding.

6 Robustness

6.1 Alternative control group

One concern about our identification strategy is whether there are unobserved differences between interrupted and uninterrupted labs that both cause interruptions and affect labor market outcomes of lab personnel irrespective of interruptions. As a robustness test, we use as a control group personnel in labs that also had interrupted R01s but had multiple R01s. Using interrupted labs instead of uninterrupted labs allows us to adjust for factors that lead to labs having interrupted R01s, assuming those are the same for labs with one R01 and multiple R01s. It also requires personnel in multiple R01 labs to be less affected (or unaffected) by funding interruptions. Figure A1 in the Appendix shows the event studies for this robustness test. The treatment dynamics for this alternative control group are similar to those in our main results, which suggests that our results are not driven primarily by differences between labs interrupted and uninterrupted R01s.

6.2 Controlling for Resubmissions

A natural concern about these estimates is whether there are differences related to project or PI quality between the personnel of interrupted and uninterrupted labs that lead to violations of the parallel trends assumption, thus biasing our estimates. One approach we take to addressing these concerns is by using resubmissions.\footnote{We are grateful to Ian Hutchins for the suggestion.} Resubmissions are applications for funding that follow an initial unsuccessful attempt. Thus, they are a coarser version of the score the NIH awards a renewal application.\footnote{To give a sense of the coarseness of renewals, in 2009, the NIH went from allowing two resubmissions to one resubmission (in rare cases, more resubmissions were possible under either regime).} We incorporate this
information by controlling for the number of resubmissions in the CS estimator.

Figure 14 shows these results — Figure A shows ATTs without covariates and with resubmissions, and figure B does the same but for the wages of the fully attached sample. Overall, controlling for resubmissions does not change the estimates much. While we would ideally have a finer measure of renewal application quality (such as reviewer scores), this gives some indication that our results are not primarily driven by unobserved project/PI quality differences.

Figure 14: This figure shows the impact of adding controls for resubmission on the aggregated estimates of the average treatment effects (ATTs) of an interruption on three mutually exclusive employment outcomes: 1) paid by a US university, 2) paid by a US non-university, or 3) not paid in the US, and the arcsine of total wages. The effects are aggregated over the 5 years after the expiration of a lab’s grant. The effects are aggregated over the 5 years after the expiration of a lab’s grant. All estimates are for individuals in a single-R01 lab, the wage regression is for the ‘Fully attached’ subsample. The estimates are obtained using a modified Callaway and Sant’Anna (2020) estimator (see Estimation section). Standard errors are bootstrapped and clustered at the R01-renewal level.

6.3 Covariate Balance
Table 6: Covariate Balance

<table>
<thead>
<tr>
<th></th>
<th>Continuously Funded</th>
<th>Interrupted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lab % Female</td>
<td>0.4583</td>
<td>0.4352</td>
</tr>
<tr>
<td></td>
<td>(0.2871)</td>
<td>(0.2954)</td>
</tr>
<tr>
<td>Lab % Asian</td>
<td>0.2704</td>
<td>0.292</td>
</tr>
<tr>
<td></td>
<td>(0.2776)</td>
<td>(0.3193)</td>
</tr>
<tr>
<td>Lab % Black</td>
<td>0.02252</td>
<td>0.03342</td>
</tr>
<tr>
<td></td>
<td>(0.08274)</td>
<td>(0.1116)</td>
</tr>
<tr>
<td>Lab % White</td>
<td>0.674</td>
<td>0.6489</td>
</tr>
<tr>
<td></td>
<td>(0.2957)</td>
<td>(0.3229)</td>
</tr>
<tr>
<td>Lab % Hispanic</td>
<td>0.04725</td>
<td>0.03959</td>
</tr>
<tr>
<td></td>
<td>(0.1217)</td>
<td>(0.122)</td>
</tr>
<tr>
<td>Lab % US-Born</td>
<td>0.5596</td>
<td>0.5744</td>
</tr>
<tr>
<td></td>
<td>(0.3248)</td>
<td>(0.3388)</td>
</tr>
</tbody>
</table>

This table shows the percent of each single-R01 lab that has particular demographic characteristics at T-1.

7 Conclusion

In this paper, we study how grant funding delays or “interruptions” affect the careers of research personnel. Using a combination of public-use grant data, university administrative data, and tax and employment data, we find that when the renewal of a Principal Investigator’s major grant – the NIH’s R01 – is interrupted, the PI’s personnel are less likely to work in the US in the long-term, and are less likely to work at a university in the first two years after interruption. Those who remain employed in the US also earn substantially less. The results are concentrated among those less attached to universities, that is students, graduate students, postdocs, and lab staff.

From matching of these data to the 2020 Decennial Census and using the UMETRICS publication match, we find that the majority of those who stop working in the US do leave the US, and the vast majority do not publish. People born in the US appear to have substantially more flexibility to move jobs – having a much greater differential response into non-US employment, to work for a different university, or to not work for a university – fitting the common understanding that visa concerns are very important for US immigrants.
In both cases, even short interruptions in funding create job instability, changing the timing of job changes and thus the potential job-match quality.

One lesson from our results is that there are costs of instability in a system even when that instability is expected. The yearly delays in passing a federal budget and the possibility of funding interruptions are issues that scientists and institutions are keenly aware of and presumably try to prepare for. As noted by one PI, “this period of gaps can be very stressful, in general it is hard to plan research in advance, when getting most of your funding in installments and uncertainty.” Yet even within our sample of research-intensive universities, the impact of funding interruptions on personnel is non-trivial. While the returns to science are yielded over years or decades (or longer), the costs to scientific workers occur on a more immediate timescale. The benefits of policies and new funding models that reduce the occurrence of similar disruptions may be understated if we focus on scientific progress without coinciding the impact on the people working in these fields.

References


Julia I Lane, Jason Owen-Smith, Rebecca F Rosen, and Bruce A Weinberg. New linked data on research investments: Scientific workforce, productivity, and public value. Research Policy, 44(9):1659–1671, 2015.


### Table A1: Effect of Interruptions on Being at Original University or Different University for Different Subsamples

<table>
<thead>
<tr>
<th>Subsample</th>
<th>At Original University</th>
<th>At New University</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>-0.0211 (0.0215)</td>
<td>0.0240 (0.0182)</td>
</tr>
<tr>
<td>Foreign-born</td>
<td>0.01766 (0.0281)</td>
<td>0.00705 (0.0224)</td>
</tr>
<tr>
<td>US-born</td>
<td>-0.0390 (0.0250)</td>
<td>0.0325 (0.0228)</td>
</tr>
</tbody>
</table>

This table shows aggregated estimates of the average treatment effects (ATTs) of an interruption on the probability of being at a person’s original UMETRICS university and of being at any other university. The coefficients should sum to the main estimate of probability of being paid by a university. The first two rows are for all single-R01 employees, while the next two are for foreign-born employees, and the last two for US-born employees. The effects are aggregated over the 5 years after the expiration of a lab’s grant. The estimates are obtained using a modified Callaway and Sant’Anna (2020) estimator. Standard errors are bootstrapped and clustered at the interrupted R01 level.
Table A2: Effect of Interruptions on Being Observed in Subsequent Decennial Censuses

<table>
<thead>
<tr>
<th>Subsample</th>
<th>In Census</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>-0.0294**</td>
</tr>
<tr>
<td></td>
<td>(0.0149)</td>
</tr>
<tr>
<td>Foreign-born</td>
<td>-0.0390</td>
</tr>
<tr>
<td></td>
<td>(0.0397)</td>
</tr>
<tr>
<td>US-born</td>
<td>-0.0157</td>
</tr>
<tr>
<td></td>
<td>(0.0183)</td>
</tr>
<tr>
<td>Faculty</td>
<td>0.0467</td>
</tr>
<tr>
<td></td>
<td>(0.0317)</td>
</tr>
<tr>
<td>Postdoc/Grad</td>
<td>-0.0234</td>
</tr>
<tr>
<td></td>
<td>(0.0393)</td>
</tr>
<tr>
<td>Other</td>
<td>-0.0432*</td>
</tr>
<tr>
<td></td>
<td>(0.0246)</td>
</tr>
</tbody>
</table>

This table shows aggregated estimates of the average treatment effects (ATTs) of in our single-R01 sample of an interruption on the probability of being found in a Decennial Census (2000, 2010, and 2020). Note that this necessarily can only contain data for Decennial Census years. The first row is for all employees of single-R01 labs, while the following rows are for subsamples of this group. The effects are aggregated over the 5 years after the expiration of a lab’s grant. The estimates are obtained using a modified Callaway and Sant’Anna (2020) estimator. Standard errors are bootstrapped and clustered at the interrupted R01 level.
Table A3: Effect of Interruptions on Publishing and Presence in 2020 Decennial Census if Absent From Tax Data

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Foreign-born</td>
<td>0.0357** (0.0173)</td>
<td>-0.00977 (0.0116)</td>
<td>-0.00774 (0.0116)</td>
<td>0.000950 (0.00631)</td>
</tr>
<tr>
<td>US-born</td>
<td>0.008823* (0.005007)</td>
<td>0.01815** (0.008856)</td>
<td>0.003393 (0.004069)</td>
<td>0.009127 (0.005595)</td>
</tr>
</tbody>
</table>

This table shows aggregated estimates of the average treatment effects (ATTs) in our single-R01 sample of an interruption on the not being found in the administrative data, split by two things: whether or not a person is observed with a publication in MEDLINE, and whether or not a person is observed in the 2020 Decennial Census. For each group, the coefficients should sum to the overall estimate of not finding people in the administrative data. The first four rows are for all foreign-born people in single-R01 labs. The second four are for US-born people in single-R01 labs. The effects are aggregated over the 5 years after the expiration of a lab’s grant. The estimates are obtained using a modified Callaway and Sant’Anna (2020) estimator. Standard errors are bootstrapped and clustered at the interrupted R01 level.
Robustness Appendix
Figure A1: This figure shows the event studies using an alternative control group, employees in labs with interrupted R01s and multiple R01s. The first row shows event studies for the three mutually exclusive placement outcomes: absent from US data, paid by a US university, and paid by a US non-university. The second row shows the event study for arcsinh-transformed wages.
Interviews with Principal Investigators of interrupted R01s

We conducted interviews with the PIs of interrupted R01s to better understand how Principal Investigators (PIs) perceive and respond to the threat of interruptions. We used the ExPORTER database to identify interrupted R01s from 2018 to 2021 and then looked up the emails of those PIs on the RePORTER website. We successfully reached six PIs in total. Three of the PIs had multiple R01s at the time of interruption, and three of the PIs had one R01 at the time of interruption. These interviews were conducted between December 2022 and February 2023.

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67 RePORTER is an online tool for searching NIH grants data.
Lab Spending from Tham (2023)

Figure A2: This figure shows the main results from Tham (2023).
Data Appendix

ExPORTER

ExPORTER is publicly available data provided by the NIH.\(^{68}\) Multiple categories of data are available on ExPORTER: Projects, project abstracts, publications, link tables from projects to publications, patents, and clinical studies. We use the Projects data to calculate how long it takes for projects to be renewed, which in turn we use to define they were interrupted or not.

Defining project periods

NIH projects are assigned a core project number that is used over multiple project periods. A project period is what we would conventionally call a “grant”: some amount of funding guaranteed over a few years. At the end of each project period, the Principal Investigator (PI) of the project can apply to renew funding for that project. If the renewal application is successful, that begins a new project period. This interval between when a project period ends and when a new project period begins (after successful renewal) is the focus of this project. However, ExPorter does not provide explicit identifiers for project periods so we have to use the other information provided in ExPORTER to determine when a project period started or ended.

The funds for a project period are allocated from the NIH to the project over multiple budget periods.\(^{69}\) Each budget period is recorded as a row in the ExPorter Projects data.

For example, project number R01GM049850, led by PI Jeffrey A. Simon, was funded from FY 1996 to FY 2017, except for FY 2013. Table A4 below shows the records from its first eight years of funding. Each year the project was funded appears as a new row in the data. In the first year, the project was funded as a new project (application type 1), but then for each of the next three years was funded as a “continuation” (application type 5). The project is then funded as a “renewal” (application type 2) in FY 2000, then again as a

\(^{68}\)https://exporter.nih.gov/

\(^{69}\)This is laid out in more detail in Section 5.3 of the NIH Grants Policy Statement.
<table>
<thead>
<tr>
<th>PI Name</th>
<th>Core Project Num</th>
<th>Fiscal Year</th>
<th>Application Type</th>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simon, Jeffrey A</td>
<td>R01GM049850</td>
<td>1996</td>
<td>1</td>
<td>New</td>
</tr>
<tr>
<td>Simon, Jeffrey A</td>
<td>R01GM049850</td>
<td>1997</td>
<td>5</td>
<td>Continuation</td>
</tr>
<tr>
<td>Simon, Jeffrey A</td>
<td>R01GM049850</td>
<td>1998</td>
<td>5</td>
<td>Continuation</td>
</tr>
<tr>
<td>Simon, Jeffrey A</td>
<td>R01GM049850</td>
<td>1999</td>
<td>5</td>
<td>Continuation</td>
</tr>
<tr>
<td>Simon, Jeffrey A</td>
<td>R01GM049850</td>
<td>2000</td>
<td>2</td>
<td>Renewal</td>
</tr>
<tr>
<td>Simon, Jeffrey A</td>
<td>R01GM049850</td>
<td>2001</td>
<td>5</td>
<td>Continuation</td>
</tr>
<tr>
<td>Simon, Jeffrey A</td>
<td>R01GM049850</td>
<td>2002</td>
<td>5</td>
<td>Continuation</td>
</tr>
<tr>
<td>Simon, Jeffrey A</td>
<td>R01GM049850</td>
<td>2003</td>
<td>5</td>
<td>Continuation</td>
</tr>
</tbody>
</table>

“continuation” the next three years. Thus, we can infer that FY 1996 to FY 1999 constituted one project period. After that, the project had to be renewed, resulting in a new project periods from FY 2000 to 2003.

The exact steps we use to determine project periods are:

1. Indicate first budget period of a new project period if application type is 1, 2, or 9.
   Define the start date of the project period as the start date of the budget period
2. Arrange budget periods by budget start date. Assign budgets that start after the first budget of a project period (as indicated by application type) to that project period, until the first budget of a new project period is reached
3. Assign the project period end date as the latest budget end date of all budget periods assigned to the project period

**Calculating time to renewal**

Our treatment variable is the time between consecutive project periods for a given R01. For each pair of consecutive project periods, we calculate this as the number of calendar days between the expiration date of the earlier project period and the renewal date of the later project period. In cases where the expiration date is after the renewal date, we redefine the expiration date to be one calendar day before the renewal date. We also use this adjusted expiration date as the reference date for defining the periods of time we use to link employees to PIs or to link PIs to their other grants (described below).
Linking PI IDs to project periods

PI IDs in ExPORTER are assigned at the row/budget period level. We assign a PI ID to a project period if a PI was assigned to any of the budget periods that constitute the project period.

Sample Construction

An ideal dataset would allow us identify employees who were part of a PI’s lab/research group that went through an R01 renewal. However, UMETRICS allows us to infer those relationships based on which employees a PI was paying around the time of renewal. The overall steps to construct our sample involve decisions at each of the following levels of data:

1. R01
2. PI-R01
3. PI-R01-employee

First, we find all pairs of expiring-renewed R01 project period pairs that were also successfully linked to UMETRICS. We keep all expiring-renewed pairs that were renewed within the same fiscal year to ensure that any observed delays in renewal were not due to unusual circumstances or data errors. This is also consistent with the NIH-level counterfactual we have in mind where the NIH funds the same projects within the same fiscal year without delay.

Next, we link the project periods in each expiring-renewed project period pair to their PI IDs. We retain all units where the PI ID appeared in both the expiring and renewed project periods. This leaves us with a set of (PI, expiring R01 project period, renewed R01 project period) triples. For simplicity, we refer to these as PI-expiring-R01 units.

Our next step is to link PI-expiring-R01 units to employees. For each PI-expiring-R01, we first fix a 12-month window that ends in the month the R01 was expiring. I.e., if the expiring month is Dec 2021, the window is from Jan 2021 to Dec 2021. We then link each PI to all their NIH grants at in that time window based on the overlap between the 12-month
window and the start and end dates of any project periods associated with the PI. This gives us a PI’s portfolio of NIH grants in the 12-month period prior to expiry.

The next step is to find employees who were part of a PI’s lab by finding employees who were paid any of the grants in this portfolio during the 12-month window. We first link the PI’s grant portfolio to a crosswalk between NIH core project numbers and UMETRICS award numbers, an identifier in UMETRICS that accompanies each transaction. Through the award numbers, we then link to the UMETRICS employee dataset to obtain all employee numbers paid through the awards in the 12-month window.

Counting R01-equivalents

To take into account that PIs with more grants may have a buffer, we measure the size of a PI’s grant portfolio based on the number of R01s they had around the time of R01 expiry. The process of constructing this measure is the same as the one for linking PIs to employees described in the previous section, except that we find all grants within a 24-month window that begins 11 months before and ends 12 months after the expiry date of the focal R01.

We include grants after expiry to allow for the possibility that PIs anticipating receiving more grants may be able or more willing to find ways to continue funding affected employees. This also assumes that the number of R01-equivalents is not affected by interruptions (i.e., not a post-treatment variable), which we think is reasonable in this context given the time lag between applying for and receiving an R01.70

Defining R01-equivalents

Given the outsized importance of the R01, we use the number of R01s and R01-equivalents as our measure of a PI’s grant portfolio. R01-equivalents are defined at the time of writing (2021) as “activity codes DP1, DP2, DP5, R01, R37, R56, RF1, RL1, U01 and R35 from

70E.g., A guide by NIAID suggests it can take 8 to 20 months upon applying https://www.niaid.nih.gov/grants-contracts/timelines-illustrated
select NIGMS and NHGRI program announcements”. However, the definition of R01-equivalent definitions can change slightly over time. We use the Internet Wayback Machine to find R01-equivalent definitions going as far back as possible (late 2017) and include all activity codes ever defined as an R01. We also include all R35 grants rather than only those from NIGMS or NHGRI, as specified in the definition, as the R35 seems to be used similarly across the NIH (to provide long-term support for outstanding investigators e.g., see https://web.archive.org/web/20211027025938/https://grants.nih.gov/grants/funding/ac_search_results.htm)

Estimating stacked data with CS estimator (Callaway and Sant’Anna, 2020)

Stacked data is usually estimated by OLS with cohort-specific unit and time fixed effects. We use the estimator developed by Callaway and Sant’Anna (2020) (“CS estimator”) because it has some desirable features such as more transparent weighting in the aggregation of group-time treatment effects, simultaneous confidence intervals, and a doubly robust modeling option. However, the CS estimator as currently implemented via the did package (Callaway and Sant’Anna, 2021) does not straightforwardly accommodate the case where controls have a well-defined “treatment” date. The rest of this section describes how we implement it.

The main issue at hand is that the did package treats all control units as being control units for all treatment cohorts, whereas in our case, control units belong to specific treatment cohorts. This means that if implemented without any modifications, for any given treatment cohort, the did package will use observations of control units from another treatment cohort in estimation. Consider, for instance, two treatment cohorts with treatments in 2000 and 2001 and units in each cohort spanning one year before and one year after (so the units...
in cohort 2000 span 1999 to 2001). The did package will compare treatment and control units belonging to the cohort 2001. However, control units from the year 2000 will also have observations in the year 2001 that did will use in estimation.

The goal is ensure that treated units within cohort are only compared to control units in the same cohort. This can be done by adding a large number to the calendar years for units in each cohort, thus artificially “separating” them from other cohorts. For instance, consider the example of two cohorts, 2000 and 2001, with the 2000 cohort spanning years 1999 to 2001 and the 2001 cohort spanning years 2000 to 2002. If we artificially add 100 years to the 2001 cohort, then it spans the years 2100 to 2102, which no longer overlaps with the 2000 cohort. Thus, the did package will no longer use observations from the 2000 cohort in 2001 for estimating effects in the 2001 cohort.

One drawback of this workaround is that it is no longer possible (or at least not straightforward) to aggregate effects by calendar years, since they have been relabelled with fake calendar years.

**UMETRICS Universities**

UMETRICS universities are research-intensive. All UMETRICS universities are classified as “R1: Doctoral Universities – Very high research activity”. UMETRICS universities are
also in the top 20% and top 25% of universities by federal R&D spending and total R&D spending respectively. Figure A3 shows the distribution of R&D spending for UMETRICS universities compared to all universities.

Source: NSF Herd Survey 2020

Figure A3: Histogram of the logarithm of total federal R&D expenditures for all universities (including UMETRICS universities) in the NSF HERD survey and for UMETRICS universities.