Online Appendix

This appendix provides additional details on the background and data of the paper, as well as supplementary results not in the main text.

1 Additional Background

1.1 Scientists' concern about uncertainty

Uncertainty over funding is a real concern among scientists. DrugMonkey, an anonymous blog run by an NIH-funded researcher, has a post titled "Never Ever Trust a Dec 1 NIH Grant Start Date". The post warns that projects that are due to be funded on December 1 - that is, on the first funding cycle of the fiscal year - are rarely funded on time due to delays in Congress passing the budget.

Even well-established researchers report that uncertainty over funding limits their ability to do research. An article in the *San Diego Union Tribune* about the impact of NIH budget uncertainty features a prominent cancer researcher, Dr. David Cheresh, expressing that "(t)he uncertainty that the NIH feels reflects itself in my willingness to hire." Dr. Cheresh is an NIH MERIT awardee with over 70,000 citations, suggesting that even scientists with strong track records are affected by the lack of long-term budget planning.[1]

1.2 Time series of interruptions

Figure 1 suggests that the NIH does respond to delays in the federal budgeting process. For each fiscal year, the graph shows the percentage of R01 projects renewed within the same fiscal year that experienced a greater than 30-day gap between expiry and renewal.

[1] The NIH MERIT award is given to "researchers who have demonstrated superior competence and outstanding productivity in research endeavors". Citation counts comes from David Cheresh's Google Scholar profile

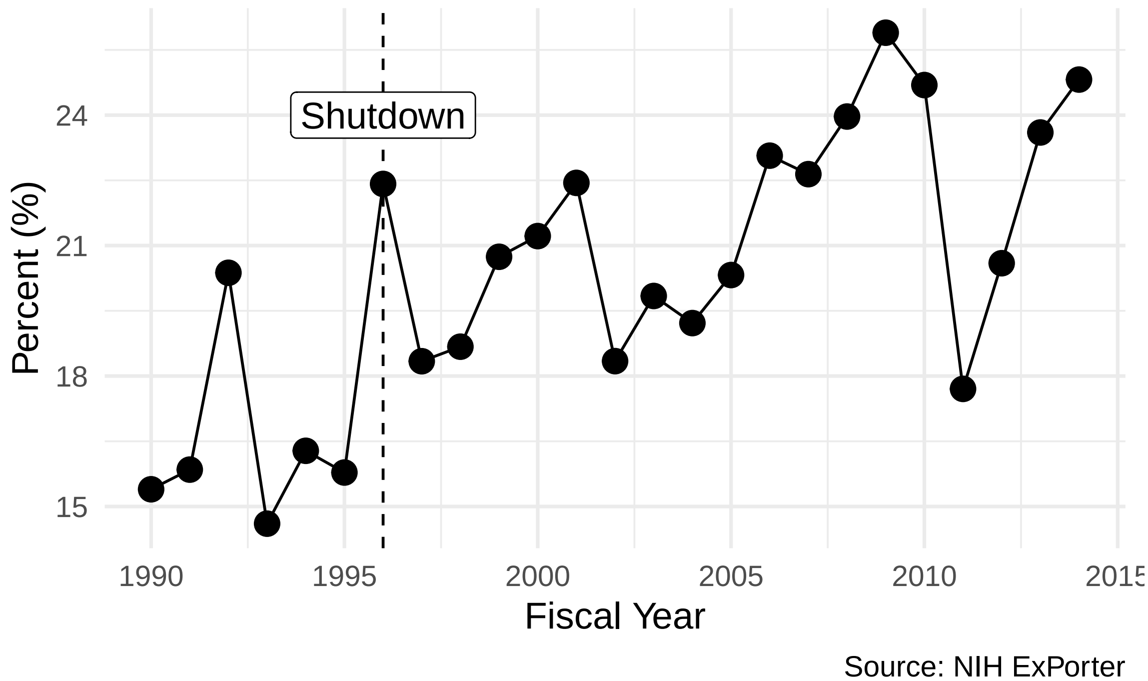


Figure 1: Proportion of renewed R01s that experienced an interruption by fiscal year. An interruption is defined as a gap in funding of more than 30 days.

1.3 Variation in interruptions across NIH Institutes and Centers

The NIH is comprised of 27 Institutes and Centers, commonly known as "ICs". Each IC is focused on a particular disease (e.g. National Cancer Institute) or body system (e.g. National Heart Lung Blood Institute). ICs administrate their own budgets and thus may choose to respond to budget uncertainty differently. The National Institute of Allergy and Infectious Diseases (NIAID), for example, describes itself as being "assiduous about issuing awards using funds from the CR (continuing resolution)."[2]

Figure 2 repeats Figure 1, showing the percentage of R01 projects that experienced a greater than 30-day gap, but for two different ICs (NIAID and NCI) rather than for the NIH as a whole. In recent years, NIAID has had a consistently lower proportion of projects experience interruptions than NCI. Even when there was an acute shock to the budgetary process during the 1996 government shutdown, both ICs appear to have responded differently, with NCI having more than 40% of its projects interrupted compared to just over 10% for NIAID.

[2] More on the organizational structure of the NIH

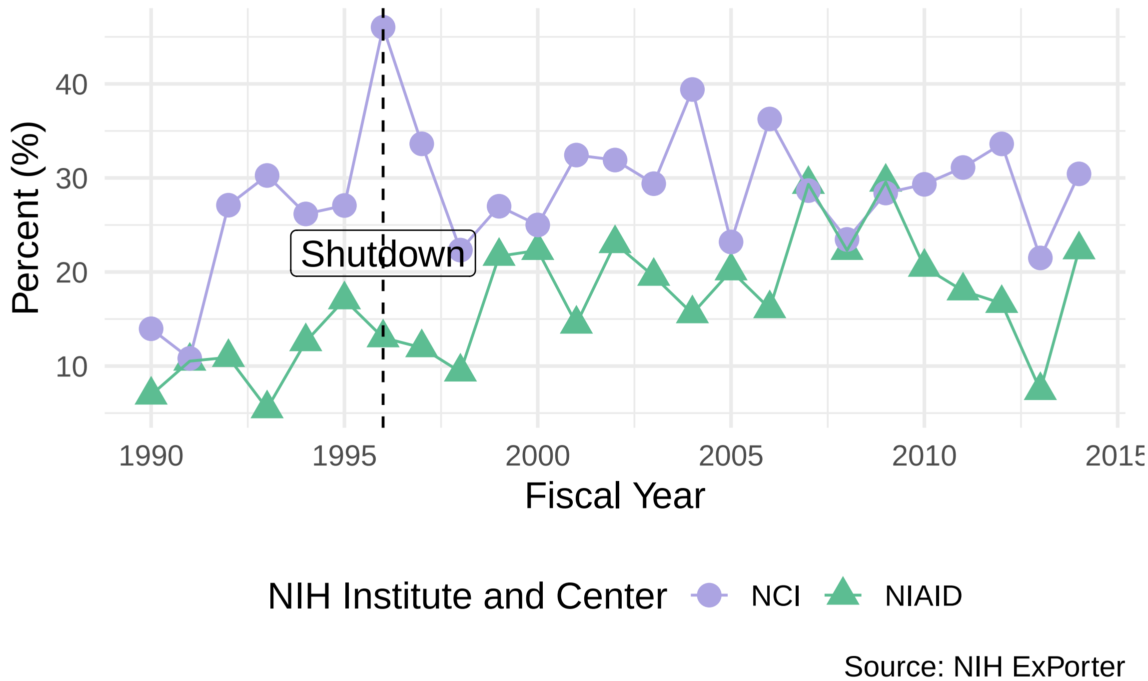


Figure 2: Variation in interruptions across NIH Institutes and Centers (ICs). The figure shows the proportion of interrupted projects by fiscal year for the National Cancer Institute (NCI) and National Institute of Allergy and Infectious Diseases (NIAID).

2 Data

The paper makes use of three main data sources.

1. NIH ExPorter
2. UMETRICS (2019 release)
3. Author-ity

2.1 NIH ExPorter

NIH ExPorter is publicly available data from the NIH that can be found at https://exporter.nih.gov/. ExPorter provides the following types of data that can be linked to each other: Projects, Project Abstracts, Publications citing support from projects, Patents citing support from projects, Clinical Studies citing support from projects

2.1.1 Defining Project Periods

NIH projects are assigned a **core project number** that is used over multiple **project periods**. The funds for a project period are allocated from the NIH to the project over multiple

budget periods.[3] Each budget period is recorded as a row in the ExPorter *Projects* data. However, ExPorter does not provide identifiers for project periods. The rest of this section explains how I construct them.

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

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

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

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

The key to defining project periods is using the *Application Type* variable.[4] This is a one-digit code that describes the type of "application" funded. For our purposes, the application type allows us to distinguish between what the NIH calls "competing" and "noncompeting" awards. "Competing" funds are provided as a result of having gone through a competitive process against other grant application. "Noncompeting" funds are provided as part of an already awarded project period. For the typical project, funds

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

disbursed in the first year (i.e. just after the application process) are competing and funds awarded in subsequent years are noncompeting.

Type	Stage
1	New
2	Renewal
3	Competing Revision
4	Extension
5	Noncompeting Continuation
6	Change of Organization Status (Successor-in-Interest)
7	Change of Grantee or Training Institution
8	Change of Institute or Center
9	Change of Institute or Center

I identify R01 project periods as follows:

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

2.1.2 Monthly panel in UMETRICS

1. Identify R01s renewed within the same fiscal year
2. Identify all PIs associated with each renewed R01
3. For period of interest (for example, 12 months before and after R01 expiry), create a monthly panel for each PI-R01 renewal
4. Restrict panel months that (a) are covered by NIH ExPorter and (b) are covered by in all 3 UMETRICS datasets (award, vendor, subaward)
5. Restrict to expiring R01 project periods that lasted for 6 years or less
6. Restrict to PI IDs that appear in the expiring project period *and* the renewed project period

2.1.3 Yearly panel for publication outcomes

I use a similar "stacking" procedure as described above to construct a PI-R01-renewal by year panel that starts 4 years before an interruption and ends 5 years after, restricted to all interruptions that took place from 1989 to 2006. The earliest possible year in the panel is 1985, the earliest year in ExPorter. The latest possible year in the panel is 2011, so the latest possible citation for a 3-year forward citation window is from 2013, which is the final year indexed in the version of Web of Science that I use. For each treatment cohort (indexed by interruption year), I exclude units that were interrupted less than 5 years before the beginning of the cohort to reduce the possibility that previous interruptions might affect the estimates. Finally, if a PI has multiple R01s renewed within the same year, I assign the PI's interruption status based on the R01 with the longest gap between expiry and renewal.

2.1.4 NIH coverage of overall grant portfolio

My measure of PI spending is limited to spending through NIH grants. This ensures a high degree of accuracy in linking NIH PIs to transactions. As discussed in the main text, the results on whether interrupted employees continue to be paid on *any grant* are consistent with the overall set of results and thus do not give us a reason to think that there is a substantial pool of non-NIH grants being used to offset the effects of interruptions.

Other research also suggest that focusing on NIH funding provides substantial coverage of researcher funding. Funk et al. (2019) estimate that about 70% of research groups (as defined by a community detection algorithm) in the UMETRICS data rely on federal funding for 90% of their funding. Moses et al. (2005) estimate that in 2002, the NIH was by far the largest funder of biomedical resesarch, funding over $20 billion in research compared to $1.2 billion by the Department of Defense. More recent data from the Survey of Federal Funds for Research and Development show that in the life sciences, the NIH has provided about 80% of federal funding for research (basic and applied research combined) in colleges and universities since 2003.[5]

2.1.5 Negative transaction amounts in UMETRICS

Some transactions in UMETRICS are negative amounts. These can appear for a number of reasons including returns, discounts, reversing a purchase that was wrongly assigned, or

[5]Data can be accessed online through the *Table Builder* tool on the NCSES website, selecting "Research Obligations" under *Measures* and the relevant variables under *Dimensions*.

money that was unused and refunded. In general, it is not possible to separately identify these reasons. If the negative amount is related to a purchase it is also not possible to identify that purchase (e.g. in the case of discounts or returns). Thus, I treat negative amounts as occurring at the transaction date when summing up transaction amounts to the PI-month level. If expenditure in a PI-month remains negative after summing up, I assign a value of zero. In the final sample, I also exclude PIs that have an unusually high amount of negative expenditure relative to the rest of the sample. Specifically, over the 24-month period covered by the panel, I sum up across months where total expenditure was negative and then across all months where total expenditure was positive. I exclude a PI if the absolute value of total negative expenditure was greater than or equal to the absolute value of total positive expenditure. Figure **??** shows the distribution of the ratio of total negative to total positive expenditure.

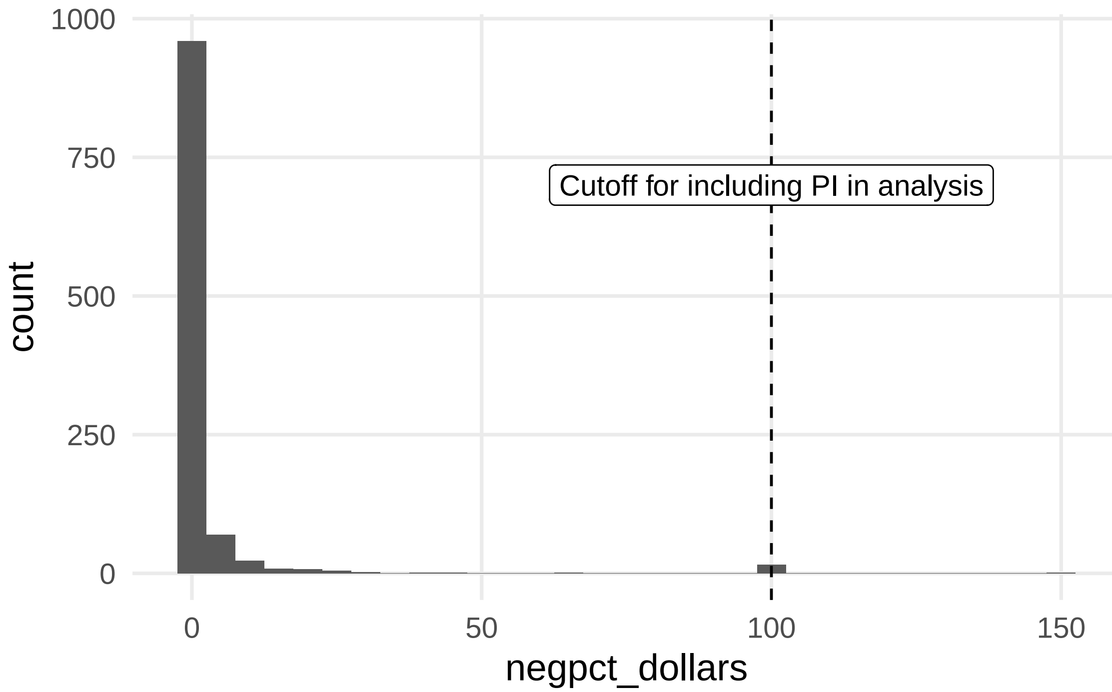


Figure 3: This is a histogram of the ratio of total negative to total positive expenditure amounts for a PI, as described in the section on negative transaction amounts in UMETRICS. The ratio is given a value of zero if total positive expenditure was zero and total negative expenditure is also zero.

2.2 UMETRICS

I use the 2019 release of the UMETRICS data set, which is housed at IRIS (Institute for Research on Innovation & Science). In this appendix I describe the most relevant components of the dataset to this paper. Additional information can be found in a summary documentation of the data is publicly available at this link. The UMETRICS Core Collection consists of administrative data from universities "drawn directly from sponsored projects, procurement, and human resources data systems". The Core Collection consists of four datasets: award, vendor, subaward, employee. "Award" data record the total expenditure from an award in a given transaction period, while the "vendor" and "subaward" data record payments to a vendor and subaward in a given transaction period respectively. "Employee" data record when an employee is paid by an award, but do not contain information on wages. In the analysis, payments to labor are backed out as the remainder after subtracting vendor and subaward payments from total expenditure (i.e. $Labor = Total - Vendor - Subaward$).

In addition to the Core Collection, there is also an Auxiliary Collection and Linkage Collection that consist of data linking the Core Collection to information such as institution characteristics or external grant data such as NIH ExPorter.

The 2019 UMETRICS release consists of data from 31 Universities. I restrict the sample to projects in institutions where transaction periods are at the monthly level. For employee data, pay periods that last longer than a month are converted to monthly, assuming employed each month contained in the quarter

2.3 Inverse hyperbolic sine

Unless otherwise stated or the outcome is a binary variable, I apply an inverse hyperbolic sine (also *asinh* or *arcsinh*) transformation to the outcome variable for all regressions, which approximates a natural logarithm and is defined at zero. The approximation is worse at smaller values (Bellemare and Wichman 2020). For "large" outcomes i.e. spending amounts, I convert estimates to percentage changes using the standard $exp(\hat{\beta}) - 1$ for log transformations. When the outcome variable is "small" (e.g. for counts of employees in a lab), I use the mean of the *arcsinh*-transformed outcome variable for interrupted PIs ($asinh(y_0)$) to back out the percentage change as follows:

$$\begin{aligned} y_1 &= sinh(\hat{\beta} + asinh(y_0)) \\ y_0 &= sinh(asinh(y_0)) \\ PercentChange &= (y_1/y_0) - 1 \end{aligned}$$

I also define a "base value" (the average for the treated/interrupted group) from which to calculate the percentage change.

3 Additional descriptive statistics and results

3.1 Spending

3.1.1 Matching on project period length

Interrupted R01s are also more likely to be 6-year R01s. To address the possibility that the estimates may be affected if R01s of different lengths have different spending trends, I repeat the analysis on PI spending using regression weights after exact matching on the length of the expiring R01 project period. The results are similar to those in the main text (Figure 4).

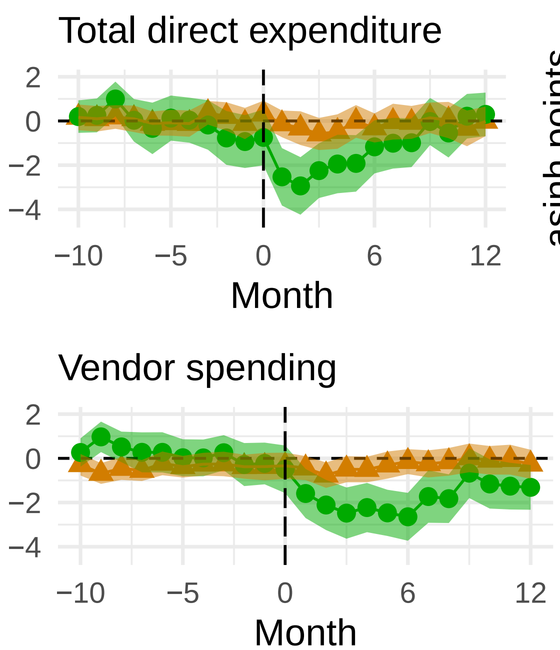


Figure 4: This figure shows event-study estimates (with 95% confidence intervals) of the difference in spending between PIs of interrupted and uninterrupted R01s, using regression weights after exact matching on expiring R01 project period length. Each panel shows the estimates for a different outcome variable: total expenditure by PI (A), total vendor expenditure by PI (B), total labor expenditure by PI (C), and total number of employees paid by PI (D). Month 0 is the month that the focal R01 expires. Month -11 is the excluded category for the regression. Regressions are run separately on subsamples of PIs that have one R01 grant (green) or multiple R01s (brown), including R01-equivalents and P01 grants. Standard errors are clustered at the PI level.

3.1.2 Spending distribution

Figure 5 shows the average *arcsinh*-transformed spending per month for interrupted and interrupted projects. For labs with one R01, uninterrupted labs decrease spending in the months before grant expiry, which then undergoes a gradual increase with the beginning of the new grant period. Interrupted labs also decrease spending before expiry but the decrease is much more pronounced. In addition, the drop in spending continues into the first month after expiry before recovering.

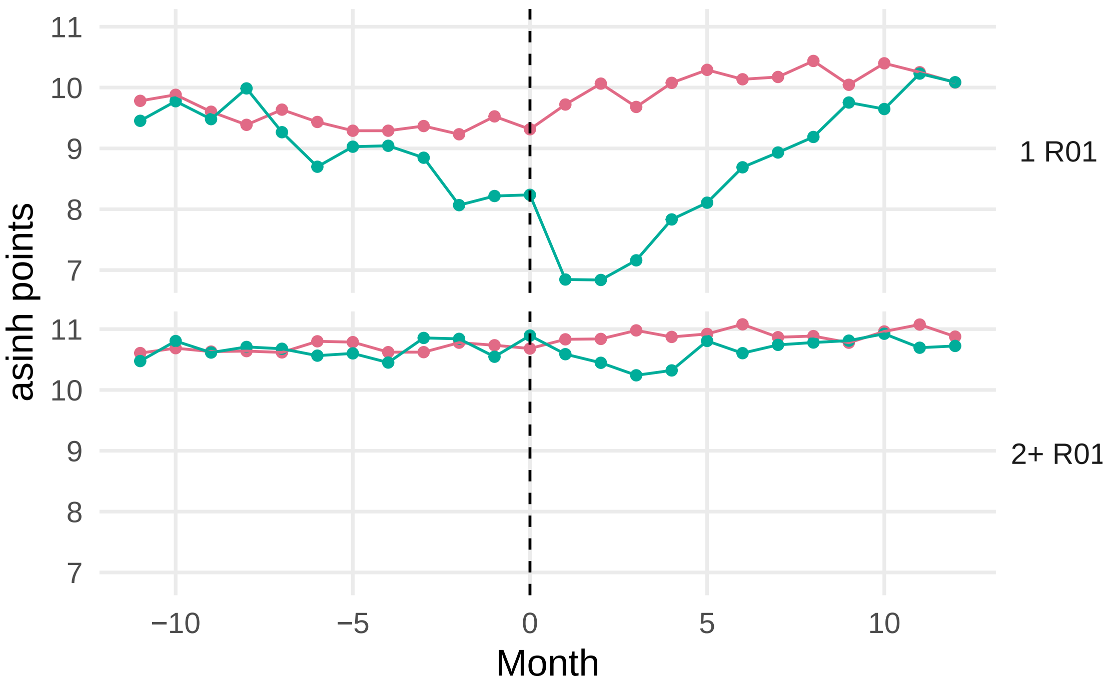


Figure 5: Average total direct expenditures (arcsinh transformed) per month for interrupted and uninterrupted projects, separately calculated for Principal Investigators with one R01 and those with at least two R01s.

3.1.3 Distribution of spending

Figure 6 shows how the entire distribution of spending changes over time. For clarity, I only show select months. The decrease in spending is driven by a "spreading" of the distribution, rather than a shifting. This results in a mass of PIs at zero, but there also remain a substantial portion of interrupted PIs that continue to spend similar amounts to uninterrupted PIs.

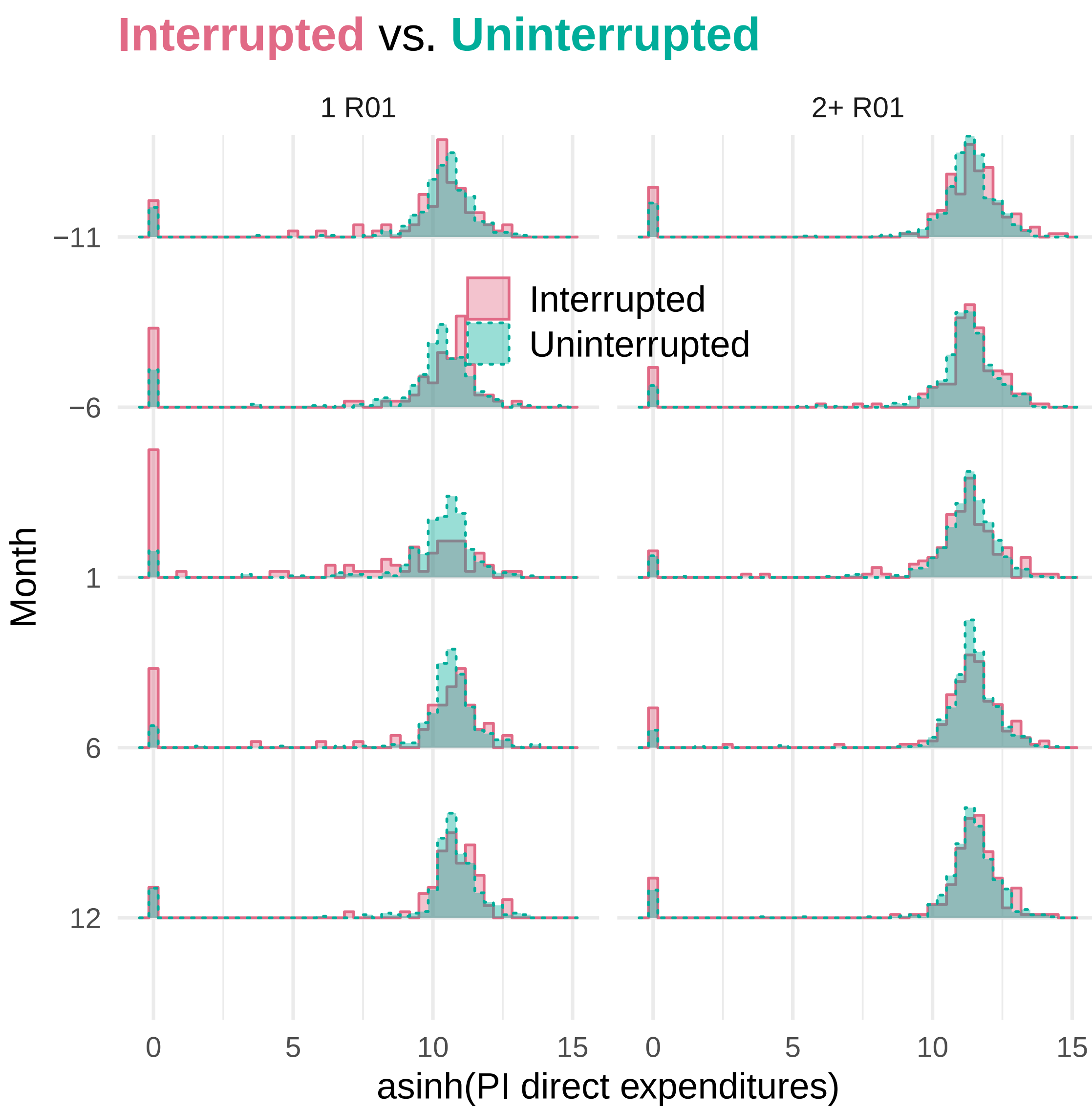


Figure 6: Histogram of total direct expenditures for each month relative to R01 expiry. Unit of observation is a PI-R01 period.

3.1.4 Length of interruption

I repeat the event-study analysis, allowing the length of the interruption to vary by estimating separate coefficients for interruptions that lasted 31 to 90 days and interruptions that were more than 90 days.

I index PIs as L, R01s as R, and the year-month as t. t_{expiry} is the year-month that the R01 grant R expires. e is the number of months before expiry i.e. $e = 0$ when R expires amd $e < 0$ before the grant expires. I restrict the sample to the one year before and after the R01 R expires, i.e. e starts at month -11 and ends at 12. $e = -11$ is excluded from the specification.

The specification is:

$$\begin{aligned} y_{LRt} = & \sum_{e=-10}^{12} \beta_{m1} \mathbf{1}(e = t - t_{expiry}) \mathbf{1}(Interrupted \in (30, 90]) + \\ & \sum_{e=-10}^{12} \beta_{m2} \mathbf{1}(e = t - t_{expiry}) \mathbf{1}(Interrupted \in (90, \infty)) + \\ & \delta_{LR} + \gamma_e + \epsilon_{LRt} \end{aligned}$$

Figure 7 displays the coefficents. For labs with only one R01, longer interruptions lead to greater drop in spending and a longer recovery. This accords with the intuition that a longer interruption would mean a longer time without access to funding. However, even in Month 3, spending does not recover completely for interruptions lasting between 31 to 90 days, indicating that even when funding becomes available, labs may need time to scale up their work again.

In addition, allowing the length of interruptions to vary reveals that even for labs with multiple R01s, spending is affected for longer interruptions. While the difference is still smaller than for labs with one R01, it is still substantial. For interruptions of more than 90 days, spending decreases by 73% at the lowest month.

3.2 Employee counts at PI/Lab-level

Table 3 displays summary statistics on the employees paid by a PI one year before R01 expiry, for the sample of PI-R01-renewals used in the main analysis of the paper.

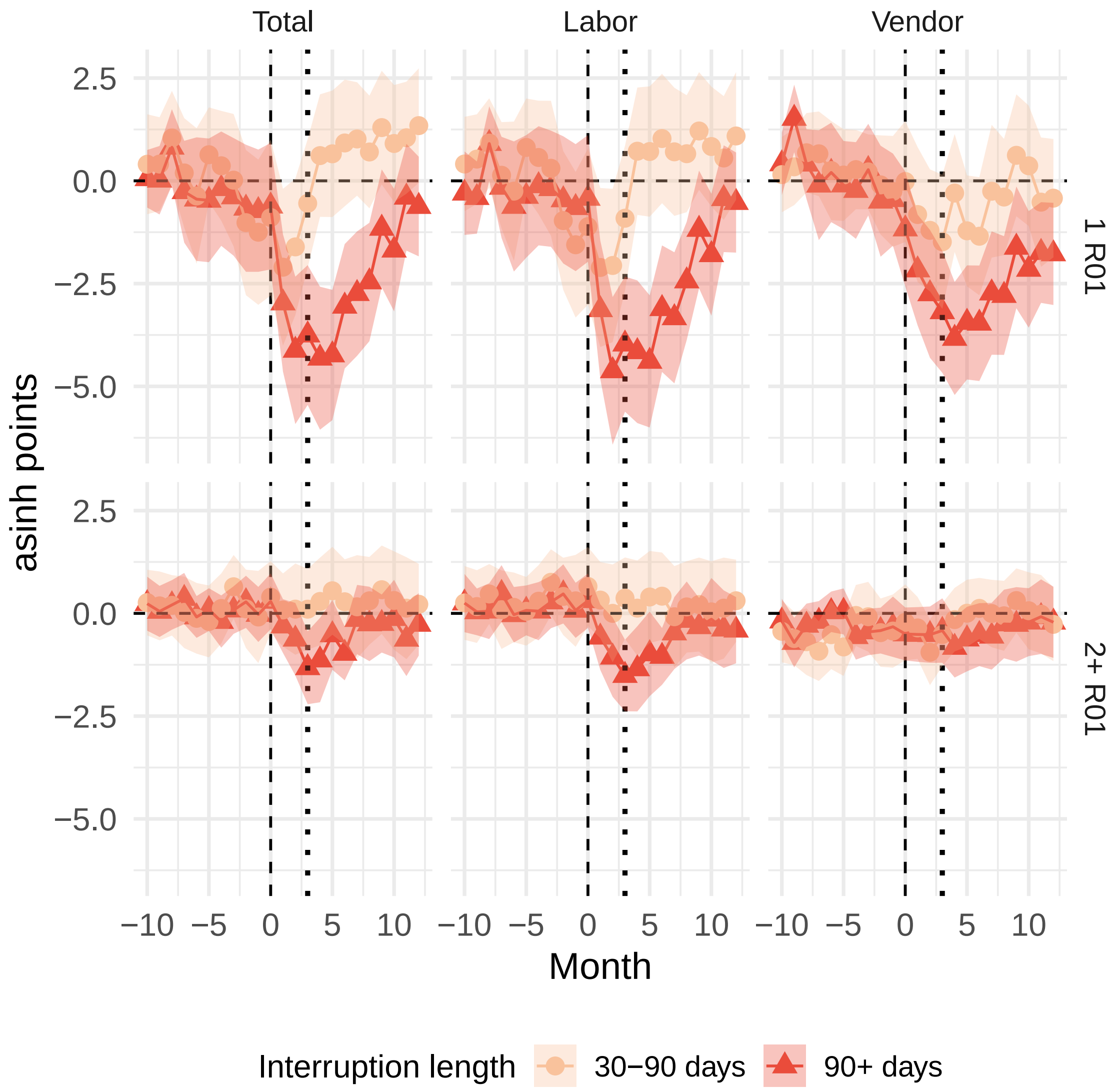


Figure 7: This graph shows event-study estimates from a balanced panel of R01-PIs 12 months before and after the focal R01's expiry month, covering a period of 24 months. Separate event study coefficients are estimated for interruptions that were 31 to 90 days and interruptions that were more than 90 days. The regressions include R01-PI fixed effects and relative-to-expiry month fixed effects. Month 0 is the month that the project's budget expires. These regressions are run separately on subsamples of PIs that have one R01 grant (top) or multiple R01s (bottom), including R01-equivalents and P01 grants. Month -11 is the excluded category for the regression. 95% confidence intervals are clustered at the PI-level.

Count of employees paid by PI at one year before expiry

		1 R01			2+ R01		
	Occupation	median	mean	sd	median	mean	sd
Count	All	4.00	5.49	6.92	8.00	11.09	14.90
	Faculty	1.00	1.48	2.11	2.00	3.16	6.18
	Postgraduate	0.00	0.65	1.49	1.00	1.30	1.91
	Research	1.00	1.15	2.08	1.00	2.53	4.64
	Clinical	0.00	0.07	0.38	0.00	0.15	1.26
	Graduate Student	0.00	0.86	1.71	0.00	1.38	2.26
	Instructional	0.00	0.02	0.15	0.00	0.06	0.35
	Other	0.00	0.10	0.43	0.00	0.15	0.55
	Other Staff	0.00	0.02	0.32	0.00	0.02	0.27
	Research Facilitation	0.00	0.62	2.21	0.00	1.59	4.12
	Technical Support	0.00	0.15	0.85	0.00	0.28	1.09
	Undergraduate	0.00	0.37	1.16	0.00	0.46	1.84

3.2.1 Event studies of employee counts by occupation

Figure 8 repeats the same analysis but using counts within occupation. I show the results for the five most common occupations: faculty, postgraduate researchers, graduate students, research, and research facilitation. Except for Research Facilitation, we see a similar pattern for all categories as we do for the total employee count.

3.3 Employee-level results

Figure 9 shows the average probability each month of being paid by the same PI and being paid by any grant at all for employees associated with interrupted and uninterrupted R01s. In both cases, the probability of being paid diverges between interrupted and uninterrupted employees. This divergence begins earlier for the “any grant” outcome.

Figure 10

3.4 Publications

3.4.1 Coarsened Exact Matching

To estimate the effect, I find all instances where an R01 was successfully renewed within the fiscal year it expires. I then stack all combinations of renewed R01s and PIs of those R01s to create an R01-PI panel.

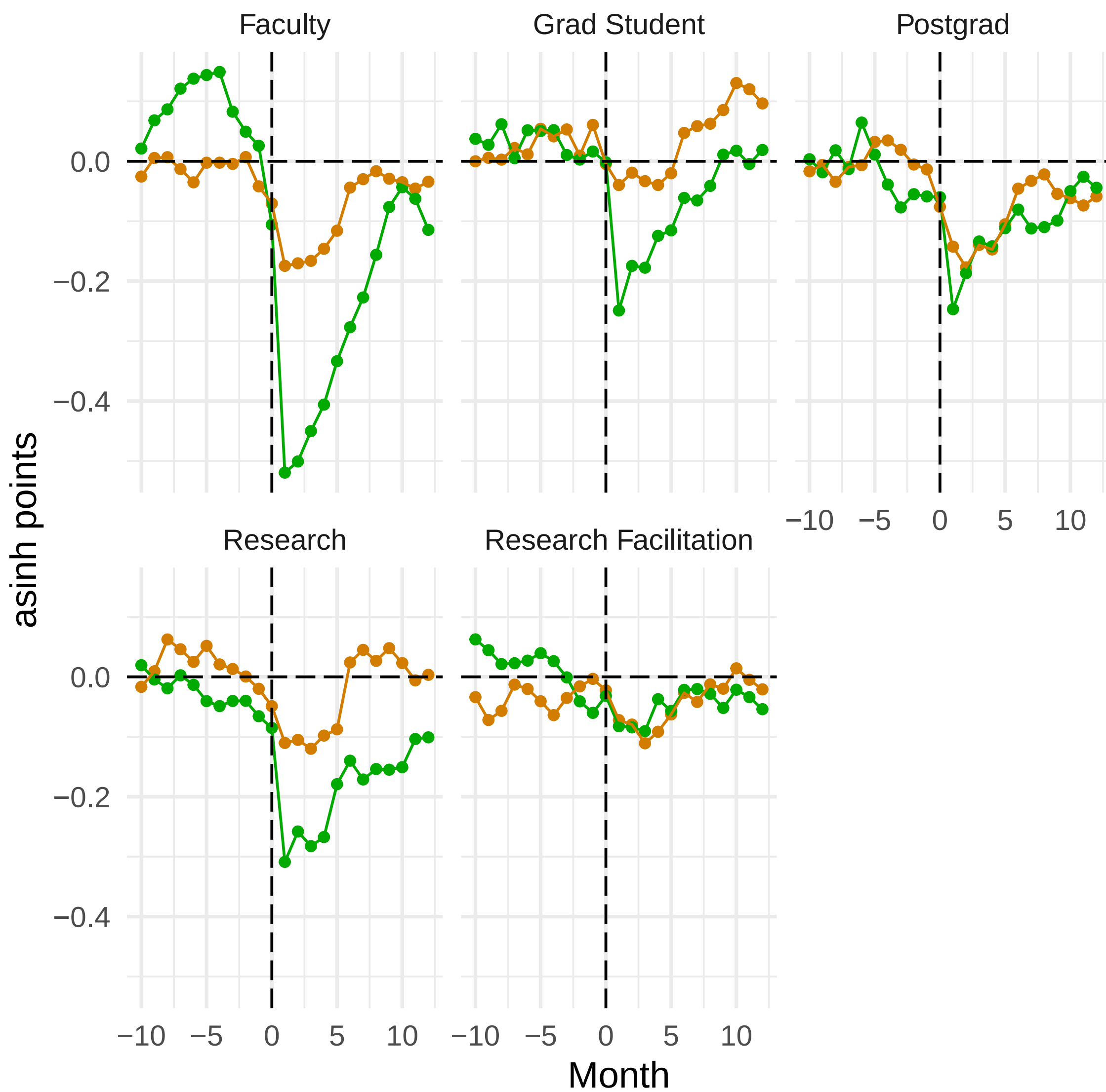


Figure 8: This graph shows event-study estimates from a balanced panel of R01-PIs 12 months before and after the focal R01's expiry month, covering a period of 24 months. The same specification is estimated for each occupation separately, where the outcome is the total number of employees of that occupation paid by the focal lab/PI. The regressions include R01-PI fixed effects and relative-to-expiry month fixed effects. Month 0 is the month that the project's budget expires. These regressions are run separately on subsamples of PIs that have one R01 grant (top) or multiple R01s (bottom), including R01-equivalents and P01 grants. Month -11 is the excluded category for the regression. 95% confidence intervals are clustered at the PI-level. Percentage changes (plotted as text) are calculated using the median number of employees for interrupted labs at month -11 as baseline.

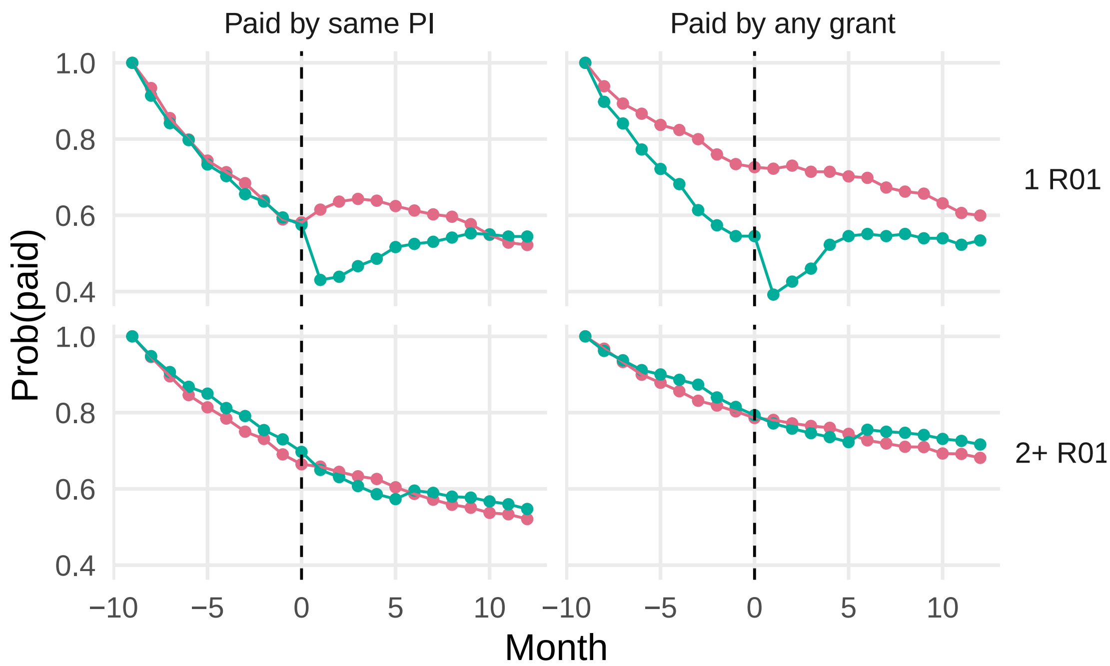
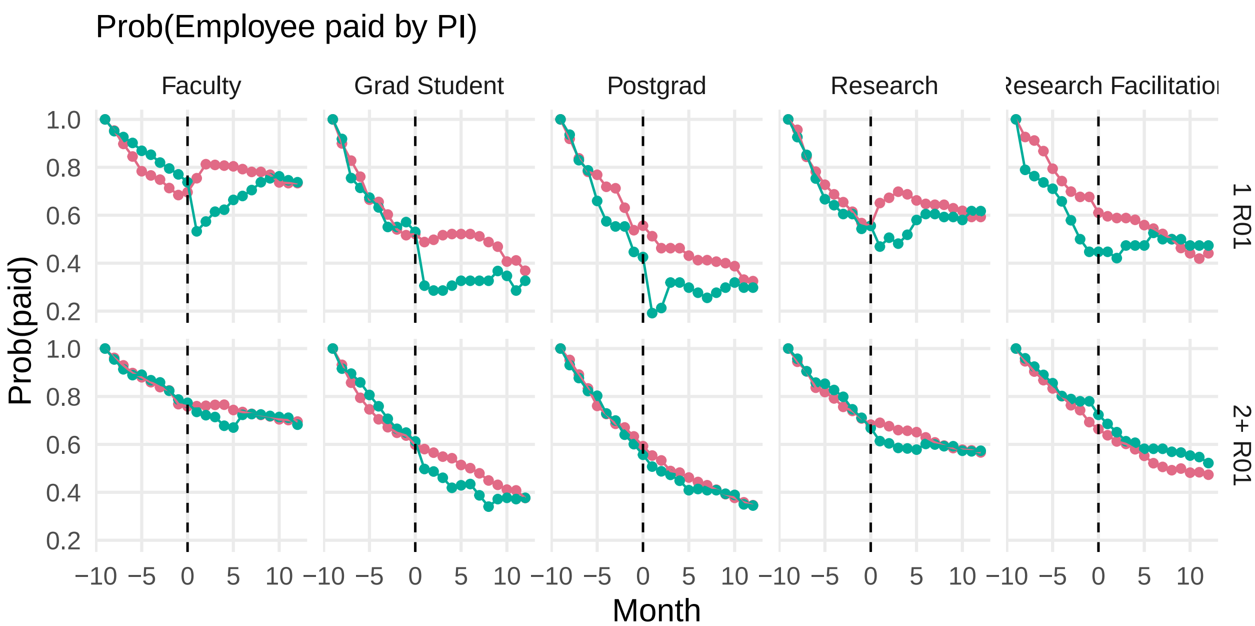


Figure 9: The left column of this figure plots the average probability every month that an employee is paid by the focal PI. The right column plots the average probability that an employee is paid by any grant at all. Employees linked to one R01 are represented in the top row. Employees linked to 2 or more R01s are represented in the bottom row.

For PI characteristics, I use Author-ity, a dataset of disambiguated author names based on a snapshot of MEDLINE in 2009, and which has been probabilistically linked to PI IDs in ExPorter through the AuthorLink dataset.

I apply Coarsened Exact Matching (Iacus, King, and Porro 2012). The variables I match on are: gender, career age at the time of R01 expiry, and publications (raw counts and weighted by 3-year forward citations) in the pre-treatment period (before R01 expiry). Career age is coarsened at 10-year intervals. Pre-treatment publications are coarsened at percentiles $0, 25, 50, 75, 90, and 95$. I then estimate event study specifications.

3.4.2 Event study



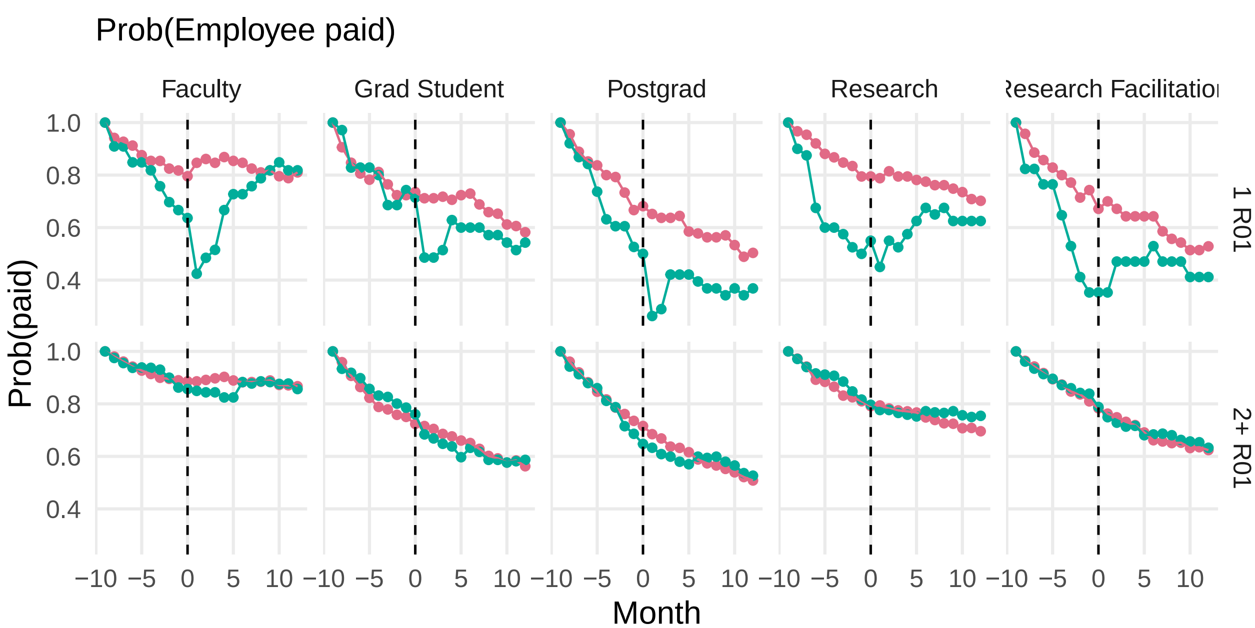


Figure 10: adsf

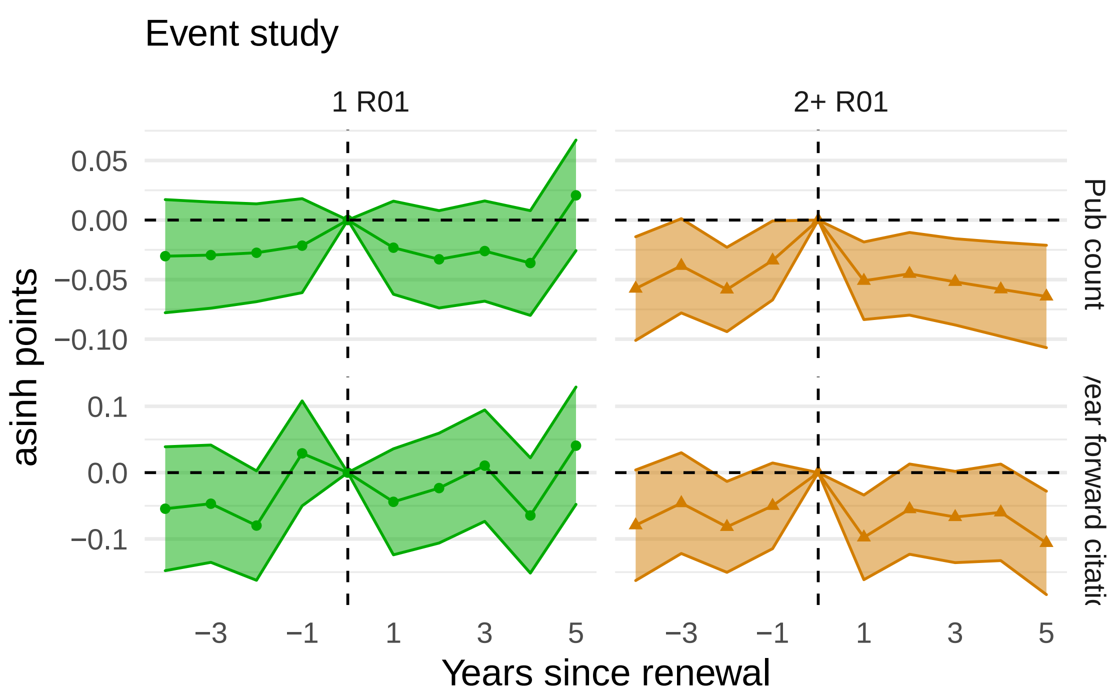


Figure 11: This figure plots the event study coefficients estimating the difference in publication counts (arcsinh-transformed) between PIs that had an interrupted R01 and PIs that had a continuously funded R01, relative to publications in the year of R01 renewal. R01-PI and treatment cohort-calendar year fixed effects included. 95% confidence intervals clustered by PI. The left/red plot is for PIs that only had one R01 and the right/blue plot is for PIs that had equivalent grants.

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