Science, Interrupted: Budget Uncertainty and Its Effects on Innovation

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Abstract

The potential for policy uncertainty to impede economic activity is a prime concern for policymakers. In recent years, the U.S. federal budget has been a major source of uncertainty. This uncertainty can induce federal agencies to delay spending till later in the fiscal year. Researchers that rely on public funding may have their funding stream interrupted as a result. Using transaction-level data on NIH-sponsored projects, I study the effect of funding interruptions on research activity. I find that researchers respond to the uncertainty from funding interruptions by reducing spending in the months leading up to the expiry of funding. Spending is substantially lower in the first month after funding resumes but recovers within 2 months, suggesting that interruptions have a disruptive effect on research even when funds become available. These findings suggest that the continuity of funding is an important factor for agencies to consider when they make research awards in addition to the quality of projects.

"The uncertainty that the NIH feels reflects itself in my willingness to hire." - David Cheresh, UCSD cancer researcher and NIH MERIT award winner

In the U.S., fiscal policy has been a prominent source of uncertainty in recent years, particularly over the federal budget (Baker, Bloom, and Davis 2016). When government agencies are uncertain about their budgets, this can cause them to engage in "precautionary savings" and shift a larger share of spending towards the end of the fiscal year (Liebman and Mahoney 2017). For research projects that rely on federal funding, this can lead to an event that I call a "funding interruption" - when a project's grant is set to expire and the arrival of new research funds is delayed. In this paper, I study the effect of funding interruptions on research activity in the context of federally-funded biomedical research.

Funding interruptions are of interest for three reasons. The first is that understanding the effect of uncertainty on research activity is important. Knowledge production is central to economic growth but may be under-invested in by private firms (Romer 1990). Direct government funding of science is one way of correcting its under-provision, and empirical evidence suggests that public sector funding has a positive return on investment (Azoulay et al. 2015). A better understanding of how uncertainty affects research activity can lead to better policy about *how*, and not just *how much*, science should be funded.

Studying interruptions also helps to overcome challenges in the study of how uncertainty affects firm behavior. One challenge is that quasi-experimental variation in uncertainty is hard to find either because firms face the same uncertainty shock, or because firm-level uncertainty and investment opportunities may be endogenous. Since not all projects experience an interruption, I am able to compare the behavior of projects that experience funding interruptions against those that do not.

Another challenge is that directly linking specific "uncertainty shocks" to a firm's behavior is difficult, in part because of the lack of high-frequency data and the unknown lags between uncertainty and firm decisions. I overcome this by using transaction-level data where we can observe economic activity at a higher frequency than is typically possible. Combining this data with data about the timing of funding interruptions allows me to focus on behavior around an observable event that occurs at a specific point in time.

To make concrete the idea of a funding interruption, consider the following example. Suppose the budget of a project is due to expire on January 31. There are three possible scenario.

1. The project is not renewed
2. The project gets more funding, and its new funding stream begins on or shortly after February 1, as soon as its previous one ends
3. The project gets more funding, but its new funding stream only begins some time after its previous one ends

For the remainder of the paper, I focus on scenarios (2) and (3). I define projects whose funding was renewed within 30 days as belonging to scenario (2) and call them "continuously funded" or "continuous" projects. Projects whose funding was renewed after more than 30 days belong to scenario (3) and are "interrupted" projects.

Using a difference-in-differences design, I find that in the 12 months prior to their official budget expiry date, interrupted projects spend 40-50% less per month than continuous projects. There are two main explanations for the divergence in spending: interrupted projects could have difficulty accessing funds to smooth their spending or are responding to the uncertainty of whether they will receive funding by stretching out their budget. These explanations are not mutually exclusive. However, spending from interrupted projects starts to decrease relative to continuously funded projects about 5-6 months before expiry, well before continuously funded projects would be able to draw on any future funding streams, implying that the stretching out of funding at least partly explains the divergence in spending.

I also find that in the first month after funding resumes, interrupted projects spend 80-90% less than continuous projects. However, monthly spending recovers within 2-3 months after funding resumes. This indicates that the funding interruption leads to a short and sharp disruption even when funding is available.

I allow the difference-in-differences estimates to vary linearly by the length of an interruption. These estimates show that the length of an interruption matters. The longer an interruption, the more pronounced the divergence in spending described above becomes.

One threat to identification is that some projects may be interrupted because they are lower quality and therefore lower prioity. If so, then the spending behavior of different projects may be driven by unobservable differences in quality. For examples, lower quality projects may be spending less because they have a harder time recruiting personnel. I use an instrumental variable to address this concern. I instrument the length of a funding gap with the average length of funding gaps for *other projects* from the same NIH institute (e.g. National Cancer Institute) that were expiring at the same time. The instrumented estimates are similar to the OLS estimates (though less precise), suggesting that differences in spending are not driven by selection.

In my final set of results, I estimate the impact of a funding interruption on research output as measured by publications. I do not find evidence that principal investigators (PIs) that experienced a funding interruption published less. I consider three explanations. First, there may indeed be no effect. Second, the transactions data does not capture funding from universities, which may be helping projects to bridge the interruption. In this case, projects are also unaffected by interruptions, but because resources have been diverted from elsewhere to ensure this is so. Third, interruptions may have a meaningful effect on publications but the variable time lag between conception and publication makes it difficult to detect that effect.

This paper lies at the intersection of three strands of literature. The first is the central question in macroeconomics of how uncertainty affects investment, employment, and economic growth. One approach to this question has been to study firm-level responses to uncertainty. Baker, Bloom, and Davis (2016) generate a measure of policy uncertainty for the U.S. using newspaper text and look at it how relates firm behavior using variation in firm reliance on government contracts. Hassan et al. (2017) and Seiler (2017) expand on this approach by directly measuring firm-level uncertainty with text from earnings conference calls and annual reports.

In public economics, this paper is related to Liebman and Mahoney (2017), who show that expiring budgets incentivize government agencies to save and spend a disproportionate share of their budgets at the end of the fiscal year. They find that this spending surge at the end of the year leads to the awarding of lower quality government IT contracts. Similarly, funding interruptions are the result of funding agencies engaging in precautionary savings when there is uncertainty about their budget or the quantity and quality of projects available to be funded.

Finally, this paper is part of a literature in innovation economics studying how uncertainty affects the productivity and choices of innovators. Azoulay, Graff-Zivin, and Manso (2011) find that scientists were more likely to produce high-impact papers and explore new research directions when they funded by an incentive scheme that was more tolerant of failure and provided regular feedback. Azoulay, Graff-Zivin, and Manso (2011) focus on a highly elite group of scientists, while the sample in this paper encompasses a broader, though still highly accomplished, part of the biomedical researcher population. This paper points out one particular reason the current system of funding may hurt risk-taking by scientists. While the insights from Azoulay, Graff-Zivin, and Manso (2011) are crucial, may not be practical to expand and therefore pointing out how improvement can be made within the current system is key.

These results highlight that when a funding agency decides to delay renewal of a project, the decision is not costless, even if the project is eventually successfully funded. This has two major implications for how we fund projects. Firstly, it suggests that there is value to having the budgets of funding agencies planned over a longer-term horizon to reduce uncertainty. Secondly, funding agencies delay projects if they expect that higher quality projects may be available later in the fiscal year. Agencies should consider that the cost of disrupting a project could prove to be bigger than the improvement in quality obtained from holding on to its funds, especially if their measures of project quality are imperfect.

1 Background and conceptual framework

1.1 National Institutes of Health (NIH)

The NIH is responsible for an annual budget of about $30 billion, much of which is disbursed through research grants. A core part of the NIH's mission is funding "basic science" aimed at generating fundamental knowledge that tend to have long-term rather than immediate impact.

The NIH comprise 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 receive their funding from Congress and administrate their own budgets.[1] This means that each IC has a new budget every fiscal year, which is typically approved in Congress along with the budgets of other federal agencies whose missions may have little relation to scientific research.

1.2 Scientist perspective

In the biomedical sciences, funding is necessary to conduct research. For a biomedical scientist that wants to run their own lab, it is key that they obtain funding through the "R01" funding mechanism. The R01 is designed to provide enough funding to establish a research career. An R01 *project period* lasts for 4-5 years, after which it must be renewed in order to receive additional funding.[2] The same *project* can last for multiple *project periods*.

Ideally, a researcher would like to maintain R01 funding for as long as possible. At the end of each project period, the principal investigator (PI) has to apply to renew their project for another project period of 4-5 years. PIs typically apply for renewal 1 to 2 years before a project period ends in order to receive funding continuously. The substantial time lag is the result of substantial uncertainty over the entire process, from preparation to submission

[1] More on the organizational structure of the NIH

[2] R01s can also be shorter (1-3 years) but this is much less common.

to acceptance or rejection. In addition to the time taken to prepare the application itself, PIs have to take into account other factors such as having to resubmit an application that is rejected the first time.

1.3 Federal budget and NIH ICs

Every fiscal year, Congress has the responsibility of passing regular appropriations bills to fund government operations (A fiscal year is identified by the year in which it ends. E.g. FY 2001 started on 1 October 2000 and ended on 30 September 2001.). This includes funding for the NIH and its ICs. If appropriations have not been made by the beginning of the fiscal year, Congress can enact a *continuing resolution* to provide temporary funding. If a continuing resolution is not enacted and a "funding gap" occurs, then federal agencies have to begin a "shutdown" of projects and activities that rely on federal funds.

It is typically taken as given that regular appropriations will not have been made by the beginning of the fiscal year on 1 October, and that federal agencies will have to operate under a continuing resolution for at least some portion of the year. Under a continuing resolution, NIH ICs continue to fund existing projects, albeit at a reduced rate. However, an IC might choose to delay funding for new or renewed projects in response to uncertainty about the federal budget since this implies uncertainty about the size of the IC's budget for the fiscal year.

1.4 Where do funding interruptions come from?

Suppose that at the beginning of the fiscal year, an IC 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 IC knows which projects it wishes to fund *and* whether it can fund them before the projects are set to run out of funding. Thus, there are no funding interruptions.

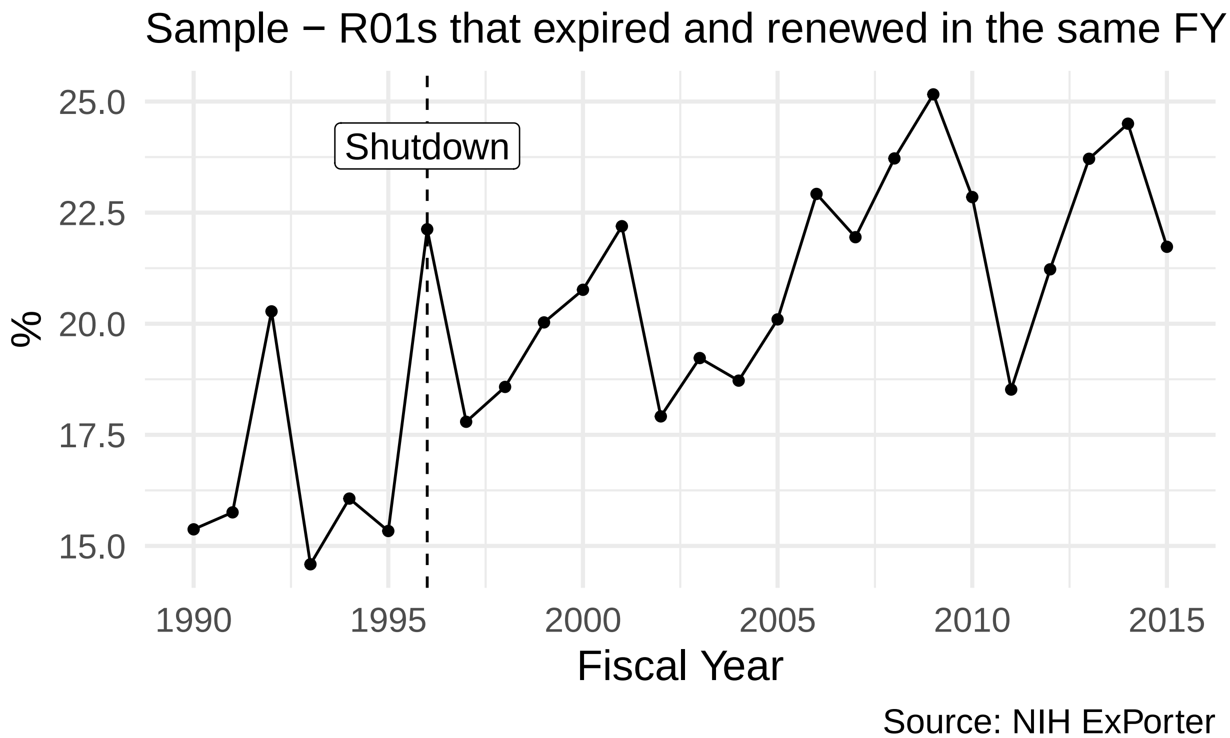

Figure 1: Average number of days between expired and renewed budget

The scenario above illustrates that funding interruptions arise from uncertainty about either (1) the IC's budget and/or (2) the quantity and quality of projects that need funding that fiscal year. Uncertainty over projects is, to some extent, inherent in the review process, which takes place over three cycles throughout the year.

Figure 1 suggests that ICs do respond to delays in the federal budgeting process. The graph shows the percentage of R01 projects that experienced a greater than 30-day gap between expiry and renewal for each fiscal year.

Since ICs have discretion in administering their budgets, they 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)". This is borne out in Figure 2.

As with Figure 1, Figure 2 shows 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

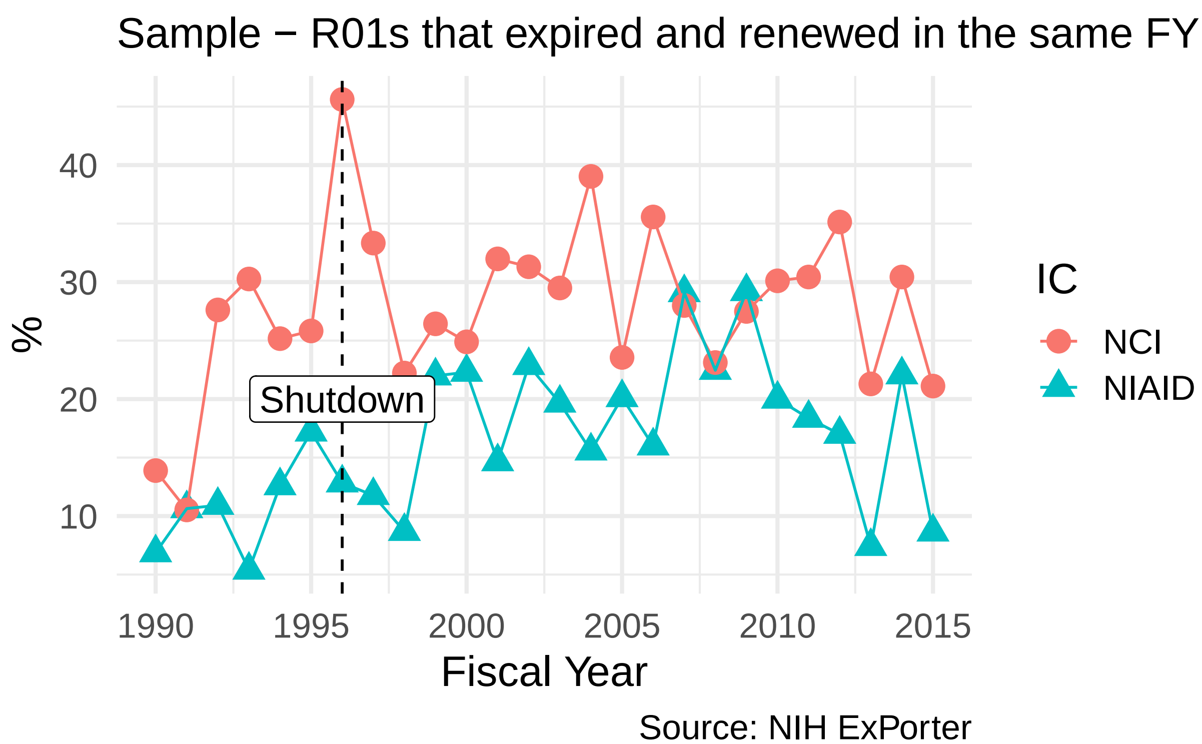

Figure 2: % interruptions for NCI and NIAID

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 in 1996, both ICs appear to have responded differently, with NCI having more than 40% projects interrupted compared to just over 10% for NIAID.

1.5 Concern in scientific community

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 theoretically 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. The quote at the beginning of this paper ("(t)he uncertainty that the NIH feels reflects itself in my willingness to hire.") comes from an NIH MERIT awardee (given to "researchers who have demonstrated superior competence and outstanding productivity in research endeavors") with over 60,000 citations.[3]

2 Data

2.1 UMETRICS

I use the 2017q4a release of the UMETRICS data, which is housed at the Institute for Research on Innovation and Science (IRIS)(Lane et al. 2015). UMETRICS core files are administrative records of transactions from sponsored projects. The data are drawn from 26 member universities. The time span covered by each university's records varies, spanning 2001 to 2017. Payments from a project can go to one of three broad categories: vendors, subawards, or personnel.

2.2 ExPorter

ExPorter is publicly available data provided by the NIH.[4] It contains data on NIH-funded projects, including identifiers that IRIS has used to link projects to their transcations in UMETRICS. Other variables relevant for this study include the IC a project is funded by, start/end dates of project budgets, and the size of the project budget.

2.3 Sample

I use these datasets to construct a project-month panel of project spending. I first limit the sample to R01 project periods that span 3-6 years (this purpose of this restriction is explained in the Empirical Strategy section). Although R01s are not awarded for more than 5 years

[3]According to his Google Scholar profile

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

initially, they can be extended an extra year if the project's funds have not been completely spent. This is otherwise known as a "no-cost extension". Under a no-cost extension, projects do not receive additional funding beyond what they were originally awarded. This sample consists of more than 11,000 project periods.

The core of the paper focuses on comparing projects that were successfully renewed, differing by whether their funding was interrupted or not. Imposing the restriction that a project had to be successfully renewed reduces the sample to over 2000 project periods.

Since each university participating in UMETRICS only provides transaction data from a fixed time period, the data are effectively truncated and sometimes we do observe the full history of transactions for a given project period. This means that the set of projects for which we observe transactions for their first year (post-renewal) is not identical to the set of projects for which we observe transactions in their last year (pre-expiry).

3 Empirical Strategy

3.1 Spending trajectory of projects

My approach is motivated in part by the empirical pattern of how projects spend their money over time.

Figure 3 shows spending over time for projects whose budgets span 3-6 years. On average, projects "ramp up" in their first 12 months and hit a peak of spending for the rest of the project until the final year, when the project starts to "ramp down". An exception to this pattern is that in a 6-year project, spending starts to decline in year 5 rather than year 6. This is due to the 6-year projects being 5-year projects originally that received a no-cost extension, thus stretching out their budget over a longer period.

I use the observed pattern of spending over a project's life cycle to motivate the idea of disruption in this context. Specficially, I focus on how spending patterns in the first and last

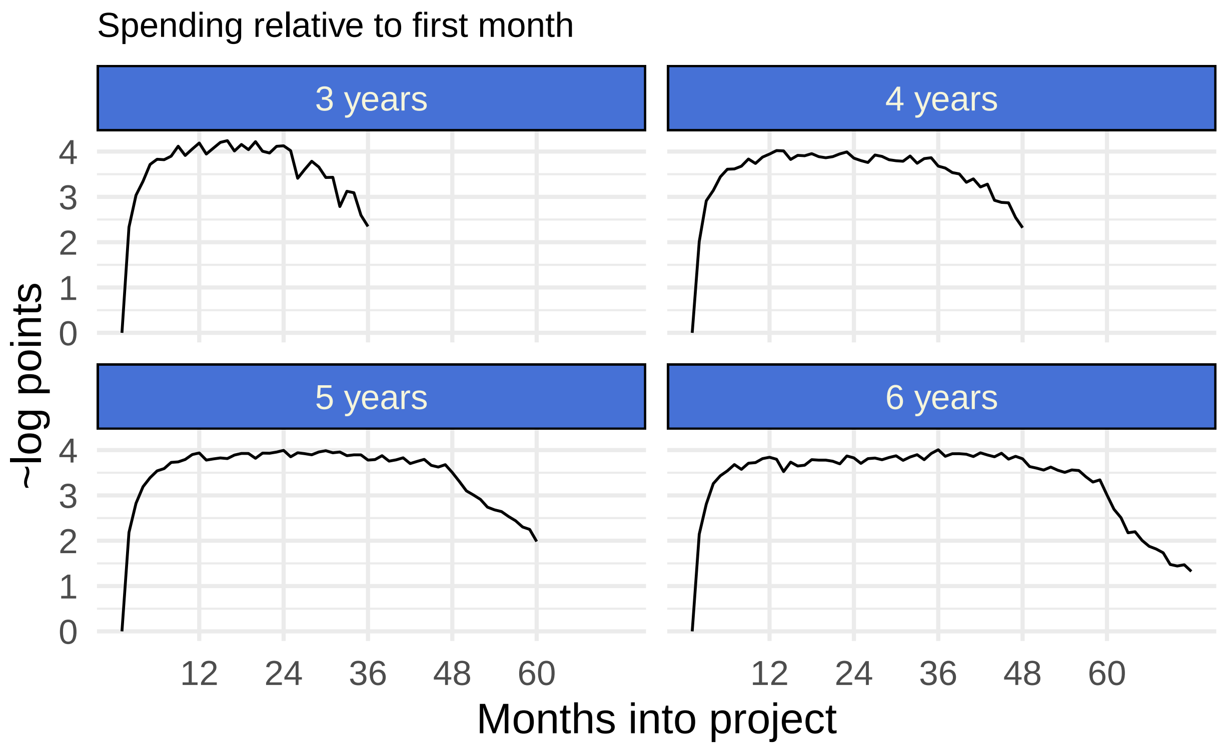

Figure 3: Spending relative to first month for projects lasting 3, 4, 5, or 6 years.

years of a project change according to how fast an IC issues grants, *relative to* peak spending in the middle years of a project. Using within-project period changes in spending helps to avoid confounding from comparing project periods with different funding amounts.[5]

Through the rest of the paper, I define an *interrupted* project as a project that faced a funding gap of more than 30 days, and a *continuous* or *continuously funded* project as a project that faced of a funding gap of 30 or fewer days.

3.2 (Binary) Difference-in-differences

I begin with a difference-in-differences approach where the differences are:

1. Difference between spending in the first year and "peak years", or between spending in the last year and peak years

[5]Even if the same project is renewed, it could be renewed with a larger or smaller budget than in the period before.

2. Comparing projects with continuous funding (renewed within 30 days) with projects that had interrupted funding (renewed after more than 30 days)

For projects of length 3 to 5 years, I define the peak years to be any years that are not the first and last years of a project. For a project period of length Y, these are months in the range $[13, 12(Y-1)]$. For 6-year projects, I define the peak to be between months 13 to 48 instead of 13 to 60, since spending already starts to decline from month 49.

Specifically, I estimate the following specification separately for continuously funded and interrupted projects,

$$ihs(spending_{p,m}) = \beta_m \mathbf{1}(m \leq 12)\mathbf{1}(M_{p,m} = m)\mathbf{1}(Gap_p > 30days) + \delta_p + \epsilon_{p,m}$$

where $ihs(spending_{p,m,y})$ is the amount of spending by project p in the mth month of its current budget, transformed by the inverse hyperbolic sine. The coefficients of interest are $\beta_m, m = 1, 2, \ldots, 12$, the difference in spending in the first 12 months of the project period. δ_p is a project period fixed effect.

$\mathbf{1}(Gap_p > 30days)$ is an indicator for whether a project experienced a funding gap of more than 30 days. Gap_p is the length of the project's funding gap.

Similarly, to estimate deviations from peak spending in the final year of a project, I leave out the first year of a project from the sample and estimate the following specification for a project period of length Y, where $Y = 3, 4, 5, 6$:

$$ihs(spending_{p,m}) = \beta_m \mathbf{1}(m \in [12(Y-1), 12Y])\mathbf{1}(M_{p,m} = m)\mathbf{1}(Gap_p > 30days) + \delta_p + \epsilon_{p,m}$$

3.2.1 Continuous difference-in-differences

I extend the difference-in-differences set up to allow the effect of funding interruptions to vary linearly with their length. This is almost identical to the specification for the binary difference-in-differences, except that I interact the treatment indicator with the length of the project's funding gap. For instance, for estimates of spending in the first year of the budget, the specification is:

$$ihs(spending_{p,m}) = \beta_m \mathbf{1}(m \leq 12)\mathbf{1}(M_{p,m} = m)\mathbf{1}(Gap_p > 30days)Gap_p + \delta_p + \epsilon_{p,m}$$

The specification for estimates for the last year of the project's budget is analagous.

3.3 Instrumental variables

One threat to identification is that if there are systematic differences between continuously funded and interrupted projects, the differences in spending may be due to those differences rather than interruptions. For example, less able PIs may be more likely to have their projects interrupted, and may be spending less because they have a harder time recruiting personnel.

To deal with this threat, I instrument the length of a funding gap with the average length of funding gaps for *other projects* from the same IC that were expiring "at the same time". I define this set of projects based on whether they would have been renewed in the same month if their new budget started one day after their previous budget expired. For example, if project p's budget expired on March 31, its best-case scenario would be to renewed on April 1. The instrument for p would be based on all projects whose best-case renewal date was in April.

The intuition behind this instrument is that if the renewal of other projects was delayed as well, then it is more likely that the focal project's delay was due to factors unrelated to productivity, such as delays in Congress passing the budget.

In notation, for a focal project p, the set of projects expiring at the same time is Q. $p \notin Q$, and the instrument is:

$$OthersGap_p = \sum_{q \in Q} Gap_q$$

where q is in the set of projects that were in the same IC as p that were expiring at the same time, excluding p.

The first-stage specification for each $m = 1, 2, ..., 12$ or $m = 12(Y-1), 12(Y-1)+1, \ldots, 12Y$ is:

$$\mathbf{1}(M_{p,m} = m)\mathbf{1}(Gap_p > 30days)Gap_p = \beta OthersGap_p\mathbf{1}(M_{p,m} = m) + \delta_p + \eta_{p,m}$$

where δ_p is a project fixed effect as before.

For this instrument to be valid, the following conditions must be satisfied:

1. the length of other projects' funding gap must be unrelated to PI or project ability (exclusion restriction)
2. the length of other projects' funding gap must explain the length of a funding gap (strong first-stage)

Condition (1) may be violated if ICs deciding to fund a project continuously means that they cannot fund another project. For example, if there are two projects, a and b, expiring in the same month and the IC is only willing to fund one continuously, then Gap_a and Gap_b are negatively correlated.

4 Results

4.1 Difference-in-differences

Figure 4 shows the estimated coefficients for continuously funded projects (blue circles) as well as for interrupted projects (red triangles). Month 0 is the month that project's budget expires, and month 1 is the month that a project was renewed.

The figure shows that even when the budget is renewed without a break (blue circle), there is a substantial decrease in spending of up that reaches its lowest point around the months of expiration/renewal and recovers towards the end of the first year of the new project period. This decrease in spending is substantial, with a 50-60% decrease relative to peak spending in

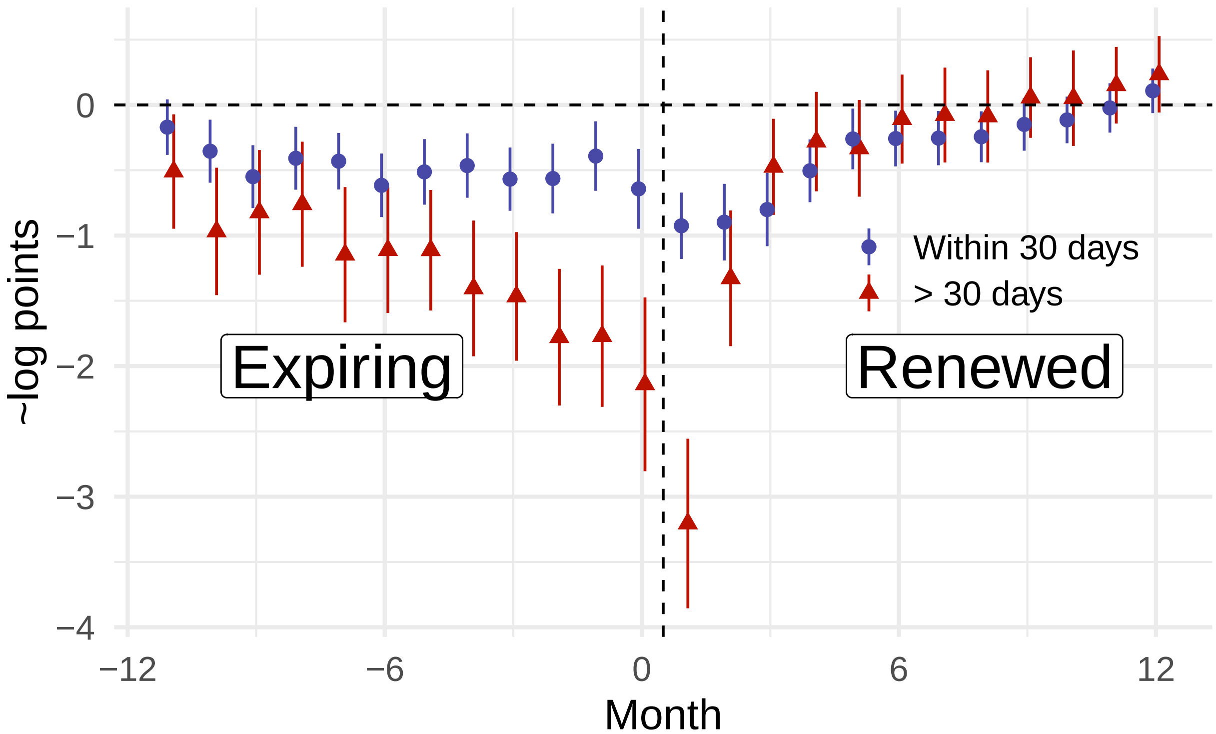

Figure 4: OLS estimates of spending in last and first years relative to peak spending. Month 0 is the month that project's budget expires

the lowest spending months.

For interrupted projects (red triangles), the decrease in spending in the expiry year is more pronounced and accelerates about 5-6 months before expiry. By the time the project's budget expires, monthly spending is about 90% less than peak spending.

After renewal of an interrupted project, spending in the first month is more than 95% lower than peak spending. However, monthly spending recovers to similar levels as a continuously funded project within two months.

There are two main explanations for the decrease in spending in the *Expiring* period. First, interrupted projects may have a harder time accessing funds than continuously funded projects. Although both types of projects are technically reaching the ends of their budgets, the funding IC may be willing to allow projects of a higher priority to spend their funds earlier. This is known as "pre-award spending", and can occur up to 90 days before the official start of the project's new budget.[6]

Second, interrupted projects may be responding to the uncertainty of whether and/or when they will receive funding by stretching the funds they have access to, assuming they have the permission to continue spending beyond the official expiration of their budget.

Since the difference in spending starts at least 5 months before the end of expiry, and pre-award spending can start at most 90 days before a new budget, the differences in spending are unlikely to be fully explained by access to funding. Thus, some of the difference in spending is likely a response to the uncertainty induced by interruptions. However, we cannot rule out access to funding as a factor as well.

The sharp decrease in spending in the first month of the *Renewed* period suggests that even when funding becomes available, interrupted projects still need time to ramp up to peak levels of activity, and are able to do so by the second or third month.

4.2 Continuous difference-in-differences

Figure 5 shows the coefficients from the continuous difference-in-difference estimation. The explanatory variable, the length of the funding gap, has been scaled so that each coefficient is the estimated effect of a 30-day interruption *relative to* being funded within 30 days. These estimates show that the decrease in spending increases with the length of an interruption, both in the Expiring and Renewed periods.

4.3 Instrumental variables

The first-stage conditional F-statistics (Sanderson and Windmeijer 2016) for the instruments are all above 100

[6] https://grants.nih.gov/grants/policy/nihgps/html5/section_7/7.9_allowability_of_costs_activities.htm

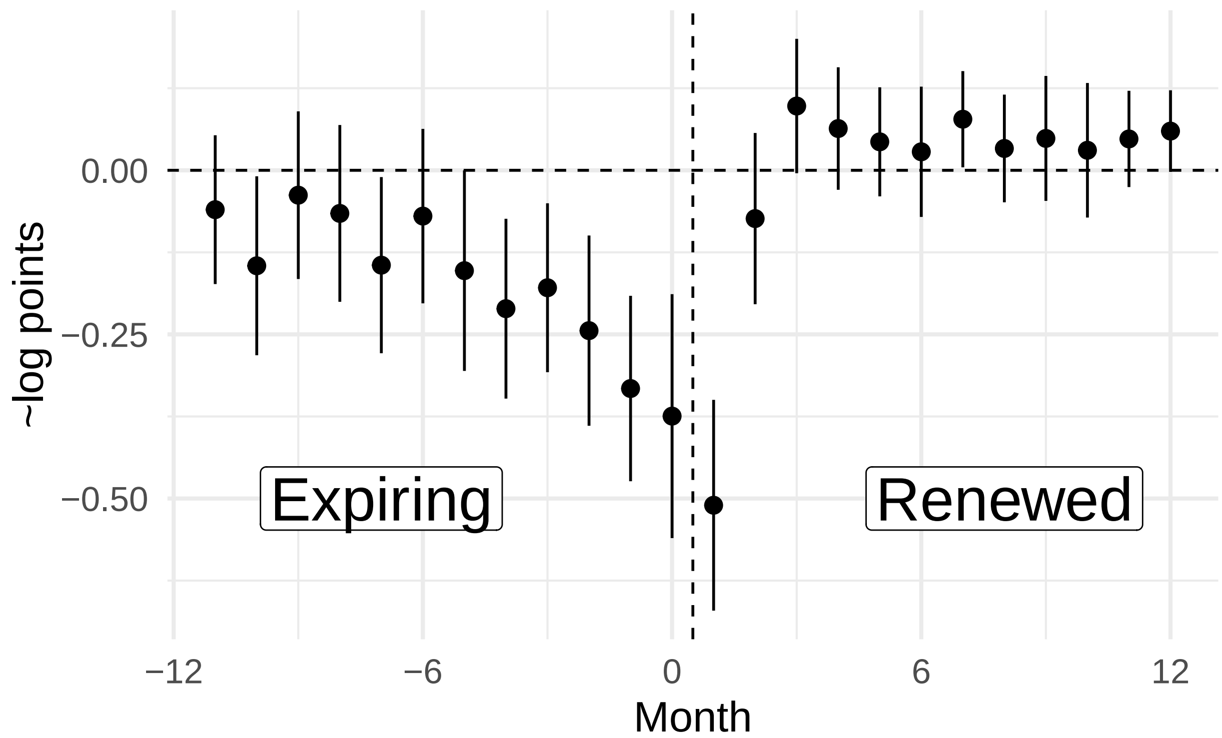

Figure 5: Continuous difference-in-difference estimates with 95% confidence intervals clustered by IC-month. Scaled to 30-day intervals. Each point is the estimated effect of a 30-day interruption relative to being funded within 30 days.

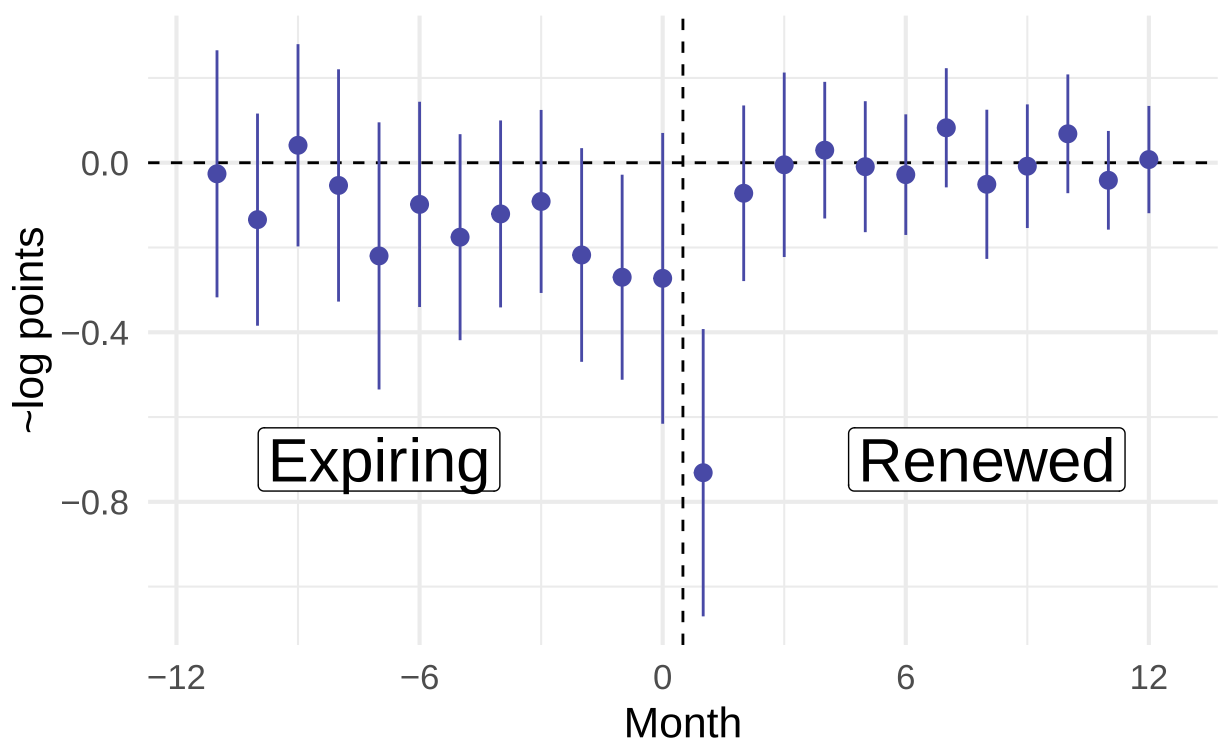

Figure 6: IV estimates with 95% confidence intervals clustered by IC-month

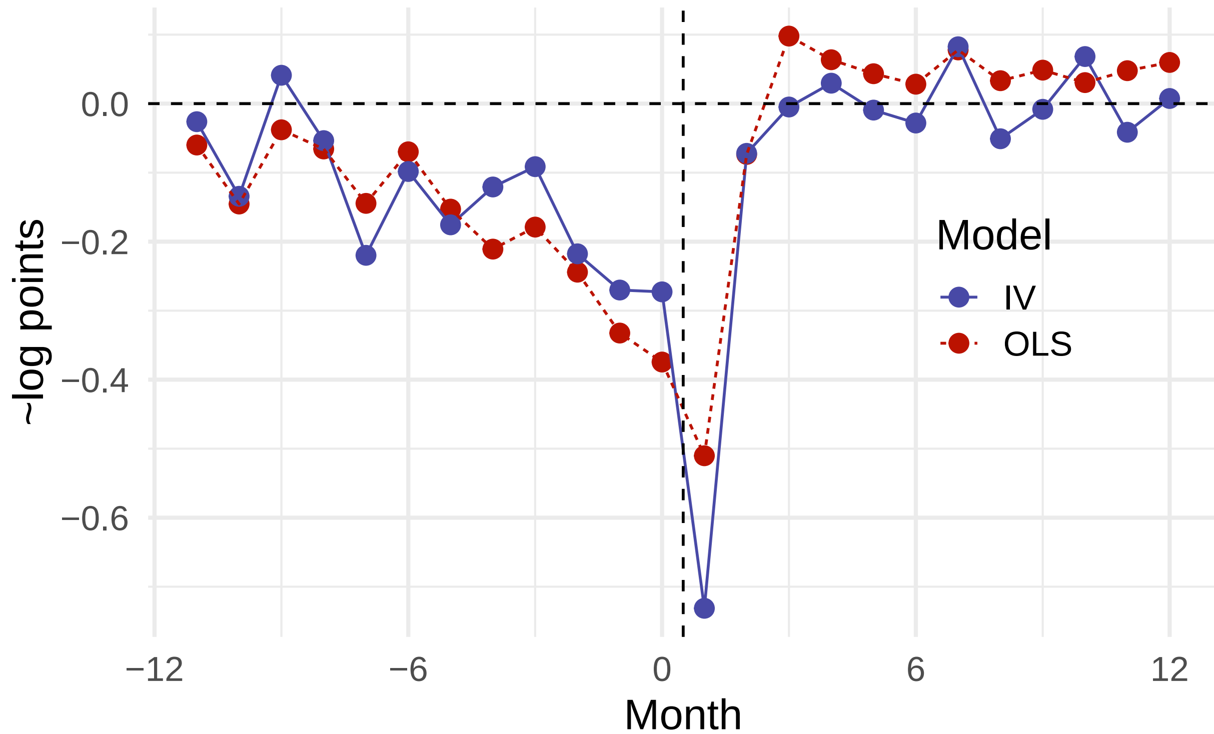

Figure 7: IV and OLS coefficients without confidence intervals

Figure 6 shows the second stage coefficients from the IV estimation with 95% confidence intervals, while Figure 7 shows the same coefficients plotted against those from the continuous difference-in-differences (Figure 5).

While the IV estimates are less precise, in terms of magnitude they show a similar pattern to the OLS estimates for the continuous difference-in-differences specification. If the IV identification assumptions hold, this suggests that the difference in spending between interrupted and continuous projects is indeed being driven by funding interruptions rather than unobserved factors.

4.4 PIs with multiple grants

A lab/PI may have multiple grants, including multiple R01s. If such a lab has its funding interrupted, it may be able to cushion the effect of an interruption by using funds from its other grants. For example, the PI may decide pay graduate students from a different grant

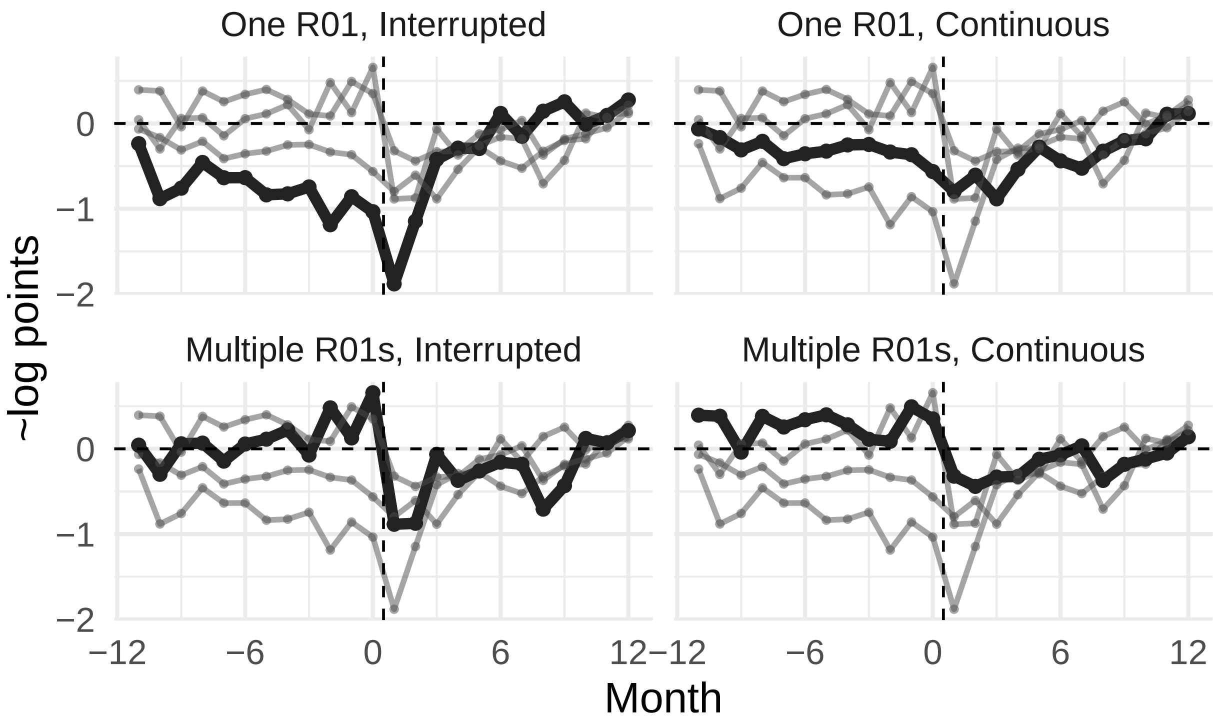

Figure 8: OLS estimates of spending in last and first years relative to peak spending, without confidence intervals. Month 0 is the month that project's budget expires. Each panel shows identical coefficients, but highlights the scenario described at the top of the panel.

until the interrupted R01 has been renewed.

To see if this happens, I perform a similar analysis with spending aggregated to the PI-level. Specifically, I identify the PI for each R01 in the data, and link total spending by that PI *from all funding sources* to the focal R01. I then re-estimate the original difference-in-differences specification separately by whether the PI of the focal R01 had another R01.

Figure 8 shows how spending evolves in one of four possible situations arising from a combination of (a) a lab having either one R01 or multiple R01s and (b) whether an R01 was interrupted or not.

Figure 9 shows the same coefficients with 95% confidence intervals. For labs with only R01, the difference in spending between interrupted and continuously funded labs remains similar to the original findings. For labs with multiple R01s, spending does not decrease in the expiry period. This indicates that PIs are able to shift spending to their other grants. However, labs with an interrupted R01 still exhibit a decrease in spending early in the renewal period

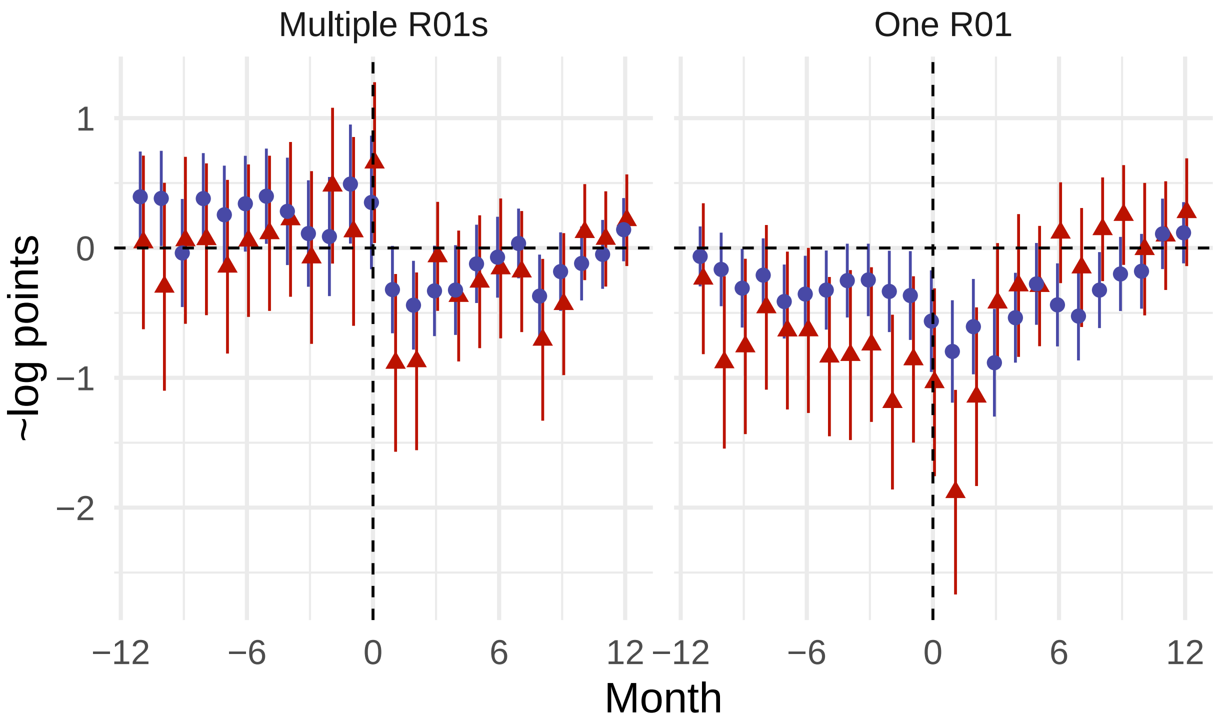

Figure 9: OLS estimates of spending in last and first years relative to peak spending, 95% confidence intervals clustered by PI. Month 0 is the month that project's budget expires.

relative to continuously funded projects, although the decrease is not statistically significant.

4.5 Effects on research output

To estimate the effect of funding restrictions on research output, I am not restricted to using the UMETRICS data on transactions, and therefore can draw on the universe of NIH-sponsored scientists over a longer time horizon.

Figure 10 does not indicate that there was any effect of having a funding interruption on the number of publications. There are 3 main explanations to reconcile

The first set of explanations is that there may indeed be no effect of funding interruptions on research output. One reason may be that funding interruptions are not disruptive enough to cause a meaningful change in research output. For instance, labs may be able to devote more time to aspects of research that can continue without spending on money (e.g. thinking of new ideas, writing).

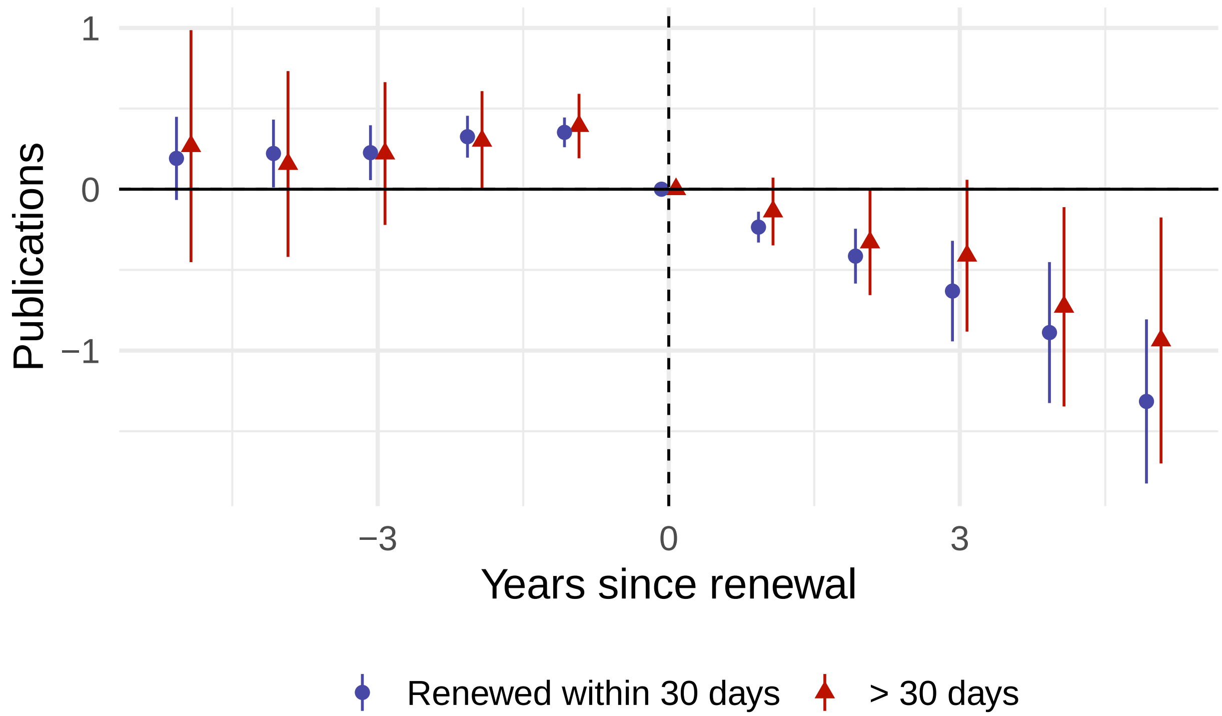

Figure 10: Effect of gaps on publications with PI and year fixed effects, 95% confidence intervals clustered by PI

Another reason is that there may be mechanisms in place to cushion the effects of a funding interruption that are not captured by the data. For example, universities may provide "bridge funding" to researchers while they are waiting for a decision from the NIH, but expenditures using university-provided funds are not captured in the UMETRICS data. In this scenario, funding interruptions would have a disruptive effect on projects in the absence of bridge funding. Even if bridge funding mitigates or even eliminates the effects of funding interruptions, resources have to be diverted from elsewhere to do so.

The second set of explanations concerns measurement. Even if funding interruptions have a meaningful effect on research output, the time lag between conception and publication is different for each publication. As a result, the effect of an interruption may be "smeared" across several years and not be detectable.

5 Conclusion

In this paper, I estimate the effect of funding interruptions on research projects sponsored by the NIH. Using transaction-level data, I am able to study these effects at a level of granularity that was previously unavailable. Comparing the monthly spending of projects that were interrupted against those that were continuously funded, I find evidence that interruptions are disruptive to research. When the budget of a project is winding down, PIs spend less either because they are reacting to uncertainty by stretching out their budgets, or because are not able to draw on funds from their next budget, or both. Even after funding resumes, spending is still substantially lower in the first month.

These results point to two important policy implications. First, policies to reduce uncertainty can help us to avoid the costs of disruptive events such as funding interruptions. Second, given that some amount of uncertainty is unavoidable, how organizations choose to react to uncertainty is an important policy lever that is also more realistically adjusted. This paper shows that the risk aversion of organizations comes with costs that should factor into decision-making.

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