Cutting the Innovation Engine:

How Federal Funding Shocks Affect University Patenting, Entrepreneurship, and Publications

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Abstract

This paper studies how federal funding affects the innovation outputs of university researchers. We link person-level research grants from 22 universities to patents, publications, and career outcomes from the U.S. Census Bureau. We focus on the effects of large, idiosyncratic, and temporary cuts to federal funding in a researcher's pre-existing narrow field of study. Using an event study design, we document that these negative federal funding shocks reduce high-tech entrepreneurship and publications, but increase patenting. The lost publications tend to be higher quality and more basic, while the additional patents tend to be lower quality, less general, and more often privately assigned. These federal funding cuts lead to an increase in private funding, which partially compensates for the decline in federal funding. Together with evidence from industry-university contracts, the results suggest that federal funding cuts shift university research funding from federal to private sources and lead to innovation outputs that are less openly accessible and more often appropriated by corporate funders.

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When the U.S. government reduced the Defense Advanced Research Projects Agency's budget for funding university computer science research from $214 million to $123 million in 2004, it cited higher corporate funding for university research as one rationale (Markoff 2005). This decision represents one small contribution to a decades-long decline in U.S. research and development (R&D) investment by the federal government and a concurrent increase in R&D investment by private industry (Figure 1). Motivated by these secular changes, we ask whether declines in federal R&D funding affect the innovation outputs of academic research. We focus on universities, a research arena where federal and private funding both play important roles and where new data allow us to observe funding at the level of the individual researcher. Universities are also engines of innovation: they train future researchers and produce innovation that is crucial for economic growth (Jaffe 1989, Audretsch and Feldman 1996).

We use data from the University of Michigan's Institute for Research on Innovation and Science (IRIS) on all grants at 22 U.S. research universities. The data are transaction-level and include every employee paid by any research grant. For every researcher in each year, we observe funding from the federal government, private sector, and other sources. We link each researcher to career histories using confidential data from the U.S Census Bureau, including the universe of IRS W2 tax records. We also link them to inventors on U.S. patents and to publication authors in the PubMed database. The time frame for analysis is from 2001 to 2017.

To identify the effects of U.S. federal funding, we focus on large (at least 40%) and temporary negative shocks to aggregate federal research funding in a researcher's pre-existing narrow field of study. An advantage of our approach is that the variation stems from actual policies—Congressional budget decisions—and thus the estimates are informative about a relevant policy counterfactual in which there is less federal funding in a particular field. We provide evidence that these shocks are idiosyncratic vis-à-vis technology opportunities and are uncorrelated with the characteristics of individual researchers, alleviating concerns about endogeneity in the relationship between funding and research outcomes. Although the shocks to aggregate funding are temporary, they have an enduring impact on individual researcher funding and thus have scope to impact the innovation outputs of academic research.

In a differences-in-differences design, we compare shocked researchers' outcomes to those of never-shocked researchers. The key identification assumption is that the treatment and control groups' funding levels and innovation outcomes would have followed parallel trends in the absence of the federal funding shocks. We test this assumption by looking for pre-trends in event studies around the year of the shock. These event studies also shed light on the dynamics of the effects. Throughout the analysis, we control for unobserved researcher characteristics with fixed effects for the project's primary investigator (PI). To control for time-varying shocks at the university or department level, we also include university-department-year fixed effects.

We assess three dimensions of university research output that represent different paths for spillovers and innovation openness: high-tech entrepreneurship, patents, and publications. To our knowledge, these have never been systematically studied together in empirical work on innovation, and certainly not in a setting with rich administrative data. They capture key tradeoffs in the use and dissemination of innovation: appropriated and commercialized by the researcher herself in a new startup, patented and thus made contractible across institutions, or disseminated openly in a publication. These outcomes are important to consider together because they provide a holistic picture of an innovation's trajectory towards being useful in the economy and the academy.

We find that a negative federal funding shock reduces a researcher's chance of founding a high-tech startup by about 80% of the mean. The event study plot has no pre-trends—supporting the identification assumption—and indicates a striking downward trend after the shock. The effect is strongest among graduate students and post-docs, which is intuitive because they have the requisite skills and experience to found a high-tech startup and are in a transitional moment in their career. Anecdotally, graduate students and post-doc are responsible for the majority of universality commercialization (Lerner et al., 2022).

The negative federal funding shocks have the opposite effect on patenting, roughly doubling the chance of a researcher being an inventor on a patent. This effect is driven by faculty and graduate students. The additional patents tend to have low generality and be less cited, suggesting that they are lower quality. Finally, the shocks reduce a researcher's overall number of publications by about 15%. This effect is entirely driven by faculty, though graduate students no doubt contribute to the work behind publications. The decline in publications is driven by research with more potential impact on future knowledge, specifically publications that are relatively basic (as opposed to applied), have higher citations, and are in higher-impact journals.[1]

[1] Across all three innovation outcomes, we find no effects among research staff. Including staff—who are

We expect that researchers whose existing funding is closer to expiration will be most exposed to the shocks because they are more likely to need new funding. Indeed, all of the effects are driven by researchers without recent awards at the time of the shock. This offers further confirmation that the mechanism for our results is reduced availability of federal funding to researchers.

In sum, the idiosyncratic, large cuts to federal funding in a researcher's specific research area reduce open, impactful research and high-tech startups, while increasing lower quality patented outputs. The underlying mechanism driving these effects could be either a change to the researcher's total level of funding or a change to her composition of funding across federal and private sources.[2] We find that federal funding cuts reduce researchers' overall funding by 14%, which is less than the effect on their federal funding alone. We also find a 29% increase in researchers' private funding for fields that get any private funding. There is a similar pattern for the share of funding: event studies show no pre-trends and then marked declines in researchers' federal funding share and increases in their private funding share after the shocks. These results suggest that both changes to researchers' overall funding levels and to their composition of funding—a shift from federal to private funders—may play a role in explaining the effects of federal funding cuts on research outputs.

We next propose three non-mutually exclusive channels through which the level and the source of funds could affect research output, all of which reflect the basic idea that economic incentives are important for innovation (Stantcheva 2021). First, the decline in the overall level of researchers' funding could reduce productivity as less resources are available to conduct research and innovation. Second, the decline in federal funding could increase basic research if federal funders are more willing to fund this type of work. Finally, increased reliance on private funding may change how research is disseminated and appropriated.

All three of these channels may be at play to some degree, but the strong positive effect on

neither students nor faculty—as an occupational category provides a useful placebo group because we do not expect them to determine the direction of research or the use of research results. Their outputs could, however, be impacted by funding levels through other channels, so we include them in our main analysis.

[2]Regarding the level of funding, existing research finds mixed results; while Jacob and Lefgren (2011) show that higher NIH funding increases publication quantity and quality, Myers (2020) and Byrski et al. (2021) find – also in the health sciences – that researcher direction is relatively insensitive to funding resources and market opportunities. Regarding the funding source, Rush Holt, CEO of the American Association for the Advancement of Science and executive publisher of the Science family of journals, wrote: "Corporate research, as beneficial as it may be, is no substitute for federal investment in research" (Holt 2016).

patenting is evidence against a pure productivity story, and the large negative effect on high-tech entrepreneurship is evidence against a pure basic vs. applied story. The results are best aligned with the final channel, where a shift away from federal and towards private funding affects outputs because the two sources have contrasting contractual and incentive structures that alter researchers' objectives and constraints (Azoulay and Li 2020). While federal awards typically assert no property rights to research outcomes, private firms have incentives to appropriate research outputs and, for that reason, employ complex legal contracts with researchers. This could lead research to be more often commercialized by the private funder.

Our results on patents, entrepreneurship, and publications line up well with this appropriation channel. First, federal funding yields fewer patents, which represent a key avenue for private sector appropriation. The negative federal funding shocks also increase the chances that a patent is assigned to a private firm. Further, in matching assignee names to funder names of university researchers, we observe that over 40% of patents with private sector assignees are assigned to the company funding the research, which is much larger than the 1.6% that would be expected under random chance. Therefore, not only do federal funding cuts lead to more patenting, but privately-funded patents are more likely to be appropriated by the private sector.

Second, federal funding leads to more high-tech entrepreneurship among university researchers, who are free to use the IP for the benefit of their own companies when they are federally funded. Third, federal funding yields more publications, which are a measure of publicly disseminated research outputs. Supporting this empirical evidence, we document that actual research grant contracts between industry and academia assign broad IP rights to the private sponsor, confirming views among practitioners (NAP 1993, McCluskey 2017). In contrast, federal grants generally come with no contract at all, enabling the researcher to freely commercialize or disseminate results.

The primary contribution of this paper is to show that federal funding is important for creating open, impactful innovations and enabling researchers to take these innovations to startups. More open science has larger spillovers (Williams 2013, Murray et al. 2016) and new high-tech firms are an important source of economic growth and job creation, with many high-tech startups originating from university research (Feldman et al. 2002, Decker et al. 2014). Since the effects we show from sudden, temporary funding cuts lead to persistent changes in university researcher innovation outcomes, it is reasonable to suppose that our could generalize to broader reductions in federal funding and point to long-term implications for economic growth.

We contribute to three literatures, all of which are relevant to policy. The first concerns how funding availability affects innovation and entrepreneurship (Aghion et al., 2008, Hall and Lerner 2010). In the private sector, financial constraints have been shown to be important determinants of corporate innovation and entrepreneurship (Kerr and Nanda 2009, Howell 2017). Prior work finds that negative shocks to private funding reduce innovation (Babina et al. 2019). We find that following federal funding cuts, university researcher entrepreneurship declines while patenting increases, pointing to substitution with private funding.

The second literature addresses the tension between intellectual property rights and innovation. While patents may incentivize private firms to fund university research, these incentives go hand-in-hand with reduced spillovers (Scotchmer 1991, Walsh et al. 2005, Azoulay and Li 2020). A key rationale for government subsidy of science is that private firms cannot fully appropriate research outcomes and therefore underinvest (Nelson 1959, Arrow 1962). This can lead to benefits from funding science publicly relative to privately (Azoulay et al. 2019, Budish, Roin and Williams 2015). However, public funding might also distort inventive activity because of inelastic R&D labor supply (Goolsbee 1998) or political pressures (Hegde 2009). Our results point to innovation benefits from public funding.

Third, this paper contributes to the literature on university research. One important strand studies spillovers from university research (Belenzon and Schankerman 2013, Tartari and Stern 2021).[3] A second examines researcher training (Bettinger and Long 2005, Feldon et al. 2011, Cheng et al. 2022). Our results on career trajectories are relevant to training for three involved parties: universities are primarily responsible for training future researchers; funding institutions such as government agences often have a mission to support training; and finally firms sponsor research in part to train future employees. A third strand of literature examines how incentives and financing affect university researcher outputs (Lach and Schankerman 2008, Hvide and Jones 2018, Tabakovic and Wollmann 2019).[4] In a seminal paper, Trajtenberg et al.

[3] Also see Belenzon and Schankerman (2009), Foray and Lissoni (2010), and Åstebro et al. (2012).

[4] There is a related, nascent literature comparing public and private funding. Working papers on this topic include Guerzoni et al. (2017) and Kong et al. (2020). One related paper that also uses UMETRICS is Glennon et al. (2018). They examine whether grants with more overall funding are associated with more patents, as well as what characteristics of a team on a given grant predict higher patenting rates. Our paper is complementary but differs in several core dimensions. First, we identify causal effects using large, idiosyncratic, and temporary cuts to federal funding in a researcher's pre-existing narrow field of study. Second, we examine other outcomes besides patenting, such as high-tech entrepreneurship and publications. Third, we explore how the reliance on

(1997) assume that university research will be less appropriable and closer to science than corporate research. Building on existing work, we document an important role for federal funding, and provide evidence suggesting that federal and private research grants yield markedly different commercialization outcomes because of their divergent incentives to appropriate research outputs.

1 Data and Sample Overview

We employ rich administrative data from multiple sources to understand how federal funding availability affects university researchers' innovation outputs, spanning high-tech startup formation, patents, and publications. This section summarizes the data that we use in the analysis. A comprehensive description is in Appendix B.

We begin with information on grant employees from 22 universities that participate in the IRIS UMETRICS program.[5] These data cover all research grants at the university and every employee on each grant in years between 2001 to 2017. The data include grant expenditures by employee-year as well as other grants details including funder name. We further observe each researcher's occupation (faculty, graduate student/post-doc/research scientist, undergraduate student, or staff) and department (e.g., physics or biology). We construct a balanced panel of researchers for the years 2001-2017, with researchers observed both before and after they are paid on a grant in the UMETRICS data. Table 1 Panel A reports summary statistics for key variables, using the individual-year panel we employ in the main analysis, which contains about 18,000 individuals (see Section 2 for sample restrictions). Among the researchers, 16.4% are faculty, 43.2% are graduate students, post-docs or research scientists, 8.1% are undergraduates, and 32.3% are staff members.

The grant data also include the Catalog of Federal Domestic Assistance (CFDA) codes, maintained by the federal government, that identify federal assistance programs.[6] We use the

federal vs. private funders affect research outcomes.

[5]The universities in our sample from the 2018 q4 UMETRICS release are: University of Arizona, Boston University, University of Cincinnati, Emory University, University of Hawaii, Indiana University, University of Iowa, University of Michigan, Michigan State University, University of Missouri, New York University, Northwestern University, University of Pennsylvania, Penn State University, University of Pittsburgh, Princeton University, Purdue, Stony Brook University, University of Texas at Austin, University of Virginia, Washington University in St Louis, and University of Wisconsin.

[6]There are 950 CFDA codes with at least five years of funding information out of the 1,200 in the raw data

CFDA codes and funder names to determine whether the funder is a federal government agency, private firm, or other sources (state or local government, foreign government, or university). We use variation in aggregate federal funding for research by CFDA code to identify the large, temporary, negative shocks to federal funding within narrow fields that form the basis of our empirical strategy described in Section 2. Each CFDA program is related to a specific field of research. Two examples are "Cardiovascular Diseases Research," and "Agricultural Basic and Applied Research" (see below for more examples). We obtain aggregate federal funding at the CFDA program level from the Federal Audit Clearinghouse. As Table 1 Panel A shows, the amount of funding in each CFDA code measured at the individual researcher-level is highly variable. The average researcher-year gets funding from 1.4 CFDA codes (with the median being 1).

These data allow us to document patterns of funding at the individual researcher level. Table 1 Panel A shows that, across all researcher-years, 13% of research funds are from private sources. On average, 22% of researcher-years have some private funding. This varies by occupation: 21% of graduate students, 30% of faculty, and 17% of undergrads receive some private funding.[7] Figure A.1 displays histograms of the private share of funding (Panel A) and the federal share of funding (Panel B) among researcher-years that receive at least some private funding. In both panels, we see substantial variation, which is relevant for our mechanisms (Section 4) in explaining our main results presented in Section 3.

We use three measures of patenting activity based on the patent application year, described in Panel B of Table 1. The first is the number of *granted* patents on which an individual is an inventor. The average chance of a researcher in our sample being an inventor on a granted patent in a given year is 0.23%, which, as we discuss below, is large relative to the population benchmark. The high mean in our data reflects a population that is actively doing research and innovation. Intuitively, the mean is larger for faculty (0.8%) and graduate students and post-docs (0.28%), and much smaller for undergraduates (0.07%) and staff (0.06%) who do not, in general, author patents. The second measure is the number of forward citations to those patents, normalized by patent class and year, which are informative about knowledge spillovers. We define *high citation* patents as those with above-median citations in the year, among patents with at least one citation. The third measure is generality (defined in Appendix B), which is higher

(see Section 2 for our further sample restrictions). For more information, see here.

[7]These statistics are not reported in tables for brevity.

when the patent influenced subsequent innovations in a broader range of fields. We define *high generality* patents as those with above-median generality scores in the year, among patents with at least one citation.

Statistics on publications are in Panel C of Table 1. The IRIS UMETRICS program matched researchers to PubMed publications using author names and other information (PubMed, a database developed by the National Center for Biotechnology Information, contains information about biomedical journal publications).[8] We consider two measures of publication quality: the journal's impact factor and the number of forward citations, both of which are constructed using Microsoft Academic Graph. We define a journal as *high (low) impact* if the impact factor is above (below) the median in a given year, and we define a publication as *high (low) citation* if the number of citations is above (below) the median in a given year and field. We also consider two measures of the degree to which a publication is basic or applied. The first measure is a score for appliedness based on terms related to clinical research from Ke (2019). We define an *applied* (or *basic*) publication as a publication with the appliedness score above (or below) median. The second measure is an indicator variable for whether a publication is subsequently cited by any patents (Marx and Fuegi 2020).

We obtain career outcomes, shown in Panel D of Table 1, from confidential administrative data at the U.S. Census Bureau, including the Business Register (BR), the Longitudinal Business Database (LBD), IRS W-2 tax records, and the Longitudinal Employer Household Dynamics (LEHD) program.[9] The W-2 records are crucial for our setting because, unlike the LEHD, they include graduate student stipends. By linking UMETRICS individuals to these data sources, we track each person's full domestic job history. We are primarily interested in two outcomes related to knowledge spillovers. First, we define *high-tech entrepreneurship* as working at an age-zero, high-tech firm.[10] High-tech startups are known to be high-growth and are associated with innovation and knowledge spillovers. On average, the chance that a person

[8]IRIS has only matched PubMed data. Since individuals are de-identified for research use, we are not able to match to other publications. The restriction to biomedicine is a limitation for the publication results.

[9]The number of observations is smaller in the career data because not all UMETRICS individuals are matched to the Census data.

[10]High-tech entrepreneurship is the number of age zero high-tech firms a person works at in a given year. Working at a high-tech startup in a given year is a rare event, so we interpret this variable as the chance of being a high-tech entrepreneur. We do not technically use an indicator for high-tech entrepreneurship due to constraints imposed by the Census disclosure process. High-tech NAICS are defined according to the NSF classification.

is a high-tech entrepreneur in a given year is about 0.23%, which, as we explain below, is high relative to the analogous base rate in the U.S. worker population. A high base rate is to be expected given the skills and technical expertise of the population we study. Among the four occupational groups (faculty, graduate students and postdocs, undergraduate students, staff), graduate students and postdocs have the highest rates of high-tech entrepreneurship (0.25%) and faculty have the lowest (0.16%). Our second outcome is whether the individual works at a university. Unsurprisingly, about 50% of person-years in our data are employed at a university. Though not our main outcome of interest, we also examine whether the researchers in our sample work at a young firm, defined as less than five years old.[11]

2 Empirical Strategy

We are interested in the effect of federal funding availability on innovation outputs. However, this relationship is confounded by two main issues: unobserved researcher characteristics and unobserved technological shocks. First, high-quality researchers might sort into prestigious federal grants. To control for unobserved researcher characteristics, we include fixed effects for the project's primary investigator (PI) in our analysis. Second, scientific fields with more technological opportunities tend to receive more funding and produce more innovation outputs (patents, startups, and publications). To address this concern, we focus on large and temporary negative shocks to aggregate federal research funding in certain fields. The intuition is that if a researcher specializes in a particular area where she has previously received federal funding, then a sudden decline in federal funding for this area will reduce the amount of federal funding available to her. We focus on negative shocks to federal funding rather than positive shocks because they speak to the trends in declining federal funding at the aggregate level.[12]

These large shocks offer five main benefits to the analysis:

1. They are largely uncorrelated with the characteristics of individual researchers;

2. They are likely to be idiosyncratic rather than reflect technological trends;

[11] In unreported analysis, we considered employment at older incumbent firms, but find no consistent effects.
[12] In Section 3.4, we show that positive shocks yield symmetric but noisier results.

3. They do not require imposing a lag structure on the relationship between shocks and outcomes;

4. They permit visual event studies and testing for pre-trends;

5. They are policy relevant.

Before expanding on these points below, it is useful to first explain how we define large and temporary negative funding shocks to a person's narrow field. We identify events that meet the following conditions: (1) the total amount of federal funding in the field (i.e., at the CFDA level) falls by at least 40% from the previous year; (2) the decline in funding is temporary and the funding level reverts back to the pre-shock level at some later point in time; (3) there are no large positive or negative funding changes (>20% or <-20%) in the two years preceding the shock. A CFDA code with an event that meets these requirements is "treated." An employee is designated as treated if she gets more than half of her funding from one of the treated CFDA codes before the code is shocked, and is assigned to the control group if she gets more than half of her funding from the control CFDA codes.

The threshold of an at least 40% decline in funding reflects a meaningful change in funding; this is the 20th percentile of year-to-year funding changes and represents roughly 40% of the standard deviation. The results are similar using higher (e.g., -30%) or lower (e.g., -50%) cutoffs. In our data there are 61 CFDA codes with one negative shock that fits these three criteria. We consider CFDA codes that never had a large negative shock (i.e., no drops of more than 40% from one year to the next) as the control group, comprising 210 CFDA codes. These restrictions lead to a sample of about 18,000 unique individuals with 1,300 treated and 16,700 control individuals. Appendix B.2 provides more details about the CFDA data and spending shocks. The summary statistics based on this sample are described above in Table 1.

Estimating Equation. To estimate the effect of negative funding shocks on research outcomes, we use differences-in-differences models both for average effects and for event studies. For the average effect, we use the following regression equation, where i denotes the individual, p the primary investigator (PI), d the department, u the university, and t the year:

$$y_{i,t} = \beta \text{Post}_{i,t} + \delta_p[+\gamma_i] + \eta_{u,d,t} + \epsilon_{i,u,d,t} \tag{1}$$

The unit of observation is the individual-year. The coefficient of interest β is on an indicator for the year being post-shock. We include two sets of fixed effects. In all specifications, we include PI fixed effects (δ_p), which enable us to control for the quality of the lead researcher and the particular topic under study.[13] We also include individual fixed effects (γ_i) in models that assess whether individual federal spending reacts to the shocks and in models that evaluate the effect on publications. We do not include these for high-tech entrepreneurship or patents, because it is relatively rare that a single individual has more than one of these events in the span of our data.[14] Finally, we include university-department-time fixed effects ($\eta_{u,d,t}$) in all specifications to address the concern that particular universities or departments might respond differently to federal funding shocks in a way that is correlated with research outputs or for time-varying shocks at the university or department level.[15]

To test for pre-trends and to understand the timing of any effects, we also estimate the following dynamic event-study version of Equation 1:

$$y_{i,t} = \sum_{\tau=-5}^{5} \beta_\tau D_{i,\tau} + \delta_p[+\gamma_i] + \eta_{u,d,t} + \epsilon_{i,u,d,t} \tag{2}$$

The vector $D_{i,\tau}$ is composed of dummies for each year around the shock (described above), ranging from five years before to five years after.[16] The controls are as defined above.

Shock Idiosyncrasy. Expanding on the aforementioned five benefits of this approach, we begin by showing that the shocks are exogenous to ex-ante choices of researchers and to technological opportunities. First, changes in the aggregate supply of federal funding within narrow program areas affect all researchers working in one area, and are thus arguably uncorrelated with the characteristics of individual researchers. This eliminates the degree to which, conditional on the field, researcher demand for resources could explain a relationship

[13] We define the PI of a grant as the highest-paid faculty member on the grant. If no faculty member is on the grant, the PI is the highest-paid individual on the grant.

[14] The results for patents are similar although noisier with individual fixed effects, but for entrepreneurship each individual rarely has more than one high-tech startup so there is little over-time variation within individuals.

[15] The departments are consistent across all universities, and there are 17 departments in total, such as computer science, biology, chemistry, and mathematics.

[16] The timing variable τ is zero in the year of the funding shock and for researchers who did not experience a negative shock.

between funding levels and research outcomes. In this context, one concern is that the treated and the control researchers might have some other characteristics that could send these researchers on differential trends following the treatment. To examine this, in Appendix Table A.1, we compare researchers in the control group and treated researchers (before the shocks take place) within university-field-year bins. We find that treated and control researchers' ex-ante characteristics—including funding source, funding amount, occupation composition, and the number of patents and publications—are not significantly different from one another, consistent with the shocks being idiosyncratic and orthogonal to individual characteristics.[17]

Second, the large, negative shocks are plausibly exogenous to technological opportunities that might be simultaneously shaping research outputs. Since the shocks are temporary and mean-reverting, they are more likely to be driven by political factors instead of long-term shifts in technological opportunities. For example, there is a common situation in which unexpected funding shortfalls (sometimes because of unrelated Congressional earmarks) lead agencies to temporarily cut funding to various programs. In Appendix Figures A.2, A.3, and A.4, we plot the level of funding for all CFDA areas that are in our analysis sample and are defined as having a large shock. The point surrounded by a red circle represents the year in which we identify the negative shock. These graphs depict the raw variation driving our identification strategy. While each program exhibits a unique pattern, there is clearly no broader downward trend accompanying the shocks, consistent with us having identified reasonably idiosyncratic events.

We next combine the shocks into a single event study in Figure 2. It plots the log level of funding for CFDA codes that experience negative shocks around the year of our large federal funding cuts.[18] We confirm that there is a large decline of about 0.7 in log funding amount during the year of the cut, which translates into a 50% decline relative to the mean. This aggregate (CFDA-level) funding decline is also temporary, reverting to the pre-shock level less than three years after the shock. Importantly, there is no consistent pre-trend before the shock.[19] This offers

[17]In Appendix Table A.1, we do not include Census outcomes due to constraints with the disclosure process.

[18]Specifically, this plot shows the average change in funding levels of shocked CFDAs around the year of the funding cut. The coefficients represent the results of a dynamic differences-in-differences regression at the CFDA level, comparing shocked CFDAs (treated group) with never-shocked CFDAs (control group). We include CFDA and year fixed effects. Year 0 is the year of the negative shock and we normalize the level in year -1 to zero. In Figure 2, we use -1 to normalized to zero in order to visualize the aggregate CFDA shock size in year 0, but year 0 elsewhere because changes in individual funding and outcomes are likely to occur following the aggregate funding declines.

[19]The way the shocks are defined does not mechanically explain the absence of a pre-trend. Our restriction of no other large (>20%) changes in the two-year period before the identified shock permits pre-trends over

strong evidence against the main concern of technological opportunities driving the declines in federal funding. If funding responds to technological opportunities, we should observe some response before the funding cut.

The aggregate R&D funding event study in Figure 2 displays the first necessary variation for our empirical strategy. The second necessary variation is shown in Figure 3, where we demonstrate that, after the aggregate funding in an individual's main field of study experiences a large, negative, temporary shock, the individual's own federal grant expenditure also declines relatively quickly and persistently. This figure uses Equation 2 to be consistent with the main empirical analysis. Note that many academic grants are multi-year, but the negative effect in Figure 3 reflects "compliers" who need new funding following the year of the shock. While it may be feasible for some researchers to wait and apply for new funding during the years following the aggregate funding drop, other researchers will experience interruptions to their work as, for example, graduate students move to other projects, or the team seeks alternative—including industry—funding. These one-time shocks are clearly not the same as the aggregate secular declines that motivate this paper, but we believe that their effects are relevant for thinking about policy counterfactuals with aggregate declines, because the one-time shocks have long-term implications for *individual* researcher funding and outcomes.[20]

The identification assumption is that the funding levels and innovation outcomes of individuals in the treatment group and individuals in the control group would have followed parallel trends without the federal funding shocks. While this assumption is fundamentally untestable, Figure 3 shows no evidence of pre-trends in federal funding before the shock at the individual level, suggesting that omitted variables unrelated to the funding shock (e.g., technological opportunities) are unlikely to be driving future changes in the funding levels and innovation outcomes of the affected researchers. This pattern of no differential trends in federal funding of the affected researchers is consistent with the results presented earlier in Table A.1, where we do not find significant differences in characteristics between treated and untreated researchers prior to the federal funding cuts. We also present this result using Equation 1 in Table 2 column 1. After the shock, federally funded expenditure of the affected researchers

time in which no year-to-year change exceeds 20%, or large shocks in years outside the two-year pre-period.

[20]Small delays in funding have large effects on researches who's income is provided by these funds. Using linked UMETRICS-Census data similar to this paper, Cheng et al. (2022) find that delays in the arrival of funding from renewed NIH grants disrupt research activities in the lab, spurring staff, post-docs and graduate students to seek employment elsewhere.

declines by about 28%.[21]

To further test for exogeneity, we conduct placebo tests for our main outcomes. The intuition is that if changing technological opportunities explain the results, then we should also observe effects beyond university researchers in the overall field, where private investment dominates, and federal research funding plays a small role. We show in Section 3.4 that in the narrow patent classes and industries with high-tech entrepreneurship corresponding to our shocked CFDA codes, there is no *immediate* effect of the shocks on private sector outcomes as there is on academic outcomes of individuals who rely on that funding.

Finally, the large, negative and temporary shocks to federal funding offer two benefits beyond being plausibly exogenous to both demand for funds and the "pull" of changing technological opportunities. First, we can study the full dynamics of innovation outcomes around these shocks without imposing a lag structure between shocks and outcomes. Second, these shocks are policy-relevant because the amount of federal funding each year can be chosen by the government.

3 Effects of Federal Funding Shocks on Research Outputs

This section first presents the full-sample effects of large negative federal funding shocks on our three main research outcomes (Section 3.1). We then focus on which researcher occupations drive these results (Section 3.2) and examine heterogeneity in the quality of patents and publications (Section 3.3). Finally, we present robustness tests (Section 3.4).

3.1 Main Results

Our outcome variables capture the three key dimensions of university research output that are reasonably observable and quantifiable: high-tech entrepreneurship, patents, and publications. To our knowledge, these have never been systematically studied together in empirical work on innovation. They capture the key tradeoffs in how innovation outputs are appropriated and disseminated. It can be appropriated and commercialized by the researcher herself in a new startup, it can be patented and thus made contractible across firms and institutions, or it can be

[21] Where $-28\% = e^{-0.3275} - 1$, where -0.3275 is the coefficient on "log Federal Funding" in column 1 of Table 2.

disseminated openly in a publication. These are, of course, not mutually exclusive outcomes, but they represent different paths for spillovers and the openness of innovation.

High-tech entrepreneurship is well-known to have spillover benefits and frequent ties to university research. We find that the large, negative federal funding shocks reduce the chances of a researcher founding a high-tech startup. Specifically, using Equation 1, Table 2 column 2 estimates that a negative shock reduces the chance of high-tech entrepreneurship in the years following the shock by 0.18 percentage points, which is about 80% of the mean. Since 80% of researchers' funding comes from federal sources (Panel A of Table 1), this effect implies that the availability of federal funding helps to shape the supply of high-skilled labor trained in universities to high-tech startups.

At the end of this section, we put our results in context by extrapolating them to the U.S. university researcher population. Here, we note that the effect on high-tech entrepreneurship is economically significant because the base rate in our sample is quite high relative to the population. On average, the chance that a person is a high-tech entrepreneur in a given year in our sample is about 0.23%. In the overall economy, the average rate of startup formation per worker during our sample period is 0.16%.[22] Despite their rarity, high-tech startups are crucial to new technology development and, ultimately, job creation. Decker et al. (2014) document that one-sixth of gross job creation and nearly 200% of net job creation is attributable to new firms (i.e., older firms experience net declines).

We present the event study results (Equation 2) in Figure 4. Consistent with the regression results, we see a striking downward trend in high-tech entrepreneurship after the shock to federal funding. The effect grows over time, suggesting a cumulative dimension where federal funding sets the stage for generations of new startups. There are no pre-trends in the event study, again supporting the identification assumption.

We explore other career trajectories in Appendix Table A.2. First, we consider entrepreneurship more broadly, defined as joining any new firm aged zero. This type of entrepreneurship, unlike the high-tech subset, is fairly common, representing the vast majority

[22]This is calculated using data originally from the BDS. It is the ratio of the average annual number of employees at new, high-tech startups (180,748) divided by the overall workforce (117 million). As a second benchmark, using firm-worker matched data from the Census's LEHD, Babina (2020) finds that 0.54% of workers leave incumbent firms annually to join any new firms—high-tech or not. In these data tech-tech sectors represent roughly 15% of employment (Babina and Howell 2019). Therefore, high-tech entrepreneurship rates are likely lower among workers of incumbent firms than in our sample of academic employment.

of new firms. It includes sole-proprietorships and is dominated by "subsistence entrepreneurship," such as coffee shops (Schoar 2010). In contrast with the negative effect on high-tech entrepreneurship, column 1 indicates a positive effect on broad entrepreneurship. Together with the remaining results in the paper, this points to some substitutability between academia and subsistence entrepreneurship. In columns 2 and 3, we consider joining a young firm (older than zero but less than five years old). Consistent with the previous results, we see a positive effect for all sectors (column 2), but a negative effect for high-tech sectors (column 3).

In columns 4 and 5, we find that the negative shocks reduce the chances a researcher works at a university. We consider all universities in column 4, and research-intensive doctoral universities in column 5.[23] In both cases, we find that the shock reduces the chances of working at a university by about 30% relative to the mean of 50%. This mean rate reflects students—who compose the majority of our sample—leaving university employment once they graduate. The negative effect on university employment suggests that federal research funding allows individuals to pursue an academic track, while the loss of federal funding pushes people out of academia. The difference is relevant to policy, as an important goal of some federal grant programs is to train the next generation of researchers.[24] Finally, in column 6 we show that the shocks have no significant effect on a researcher's wage.

The second key research outcome is patenting activity. Granted patents serve as a proxy for innovation with commercial application. That is, if researchers intend to have a practical private sector use for their outputs, then more productive research will likely be associated with more patents. However, patents also reflect a decision to engage in the requisite disclosure and costs associated with applying for a patent, implying intent to create contractible intellectual property; alternatives are to publish the invention as openly available science, or maintain it as a trade secret. In contrast to high-tech entrepreneurship, Table 2 shows that cuts to federal funding increase patenting, measured on the extensive margin (column 3) or using the number of patents (column 4).[25] The estimate in column 3 implies that the large, negative federal funding shocks roughly double a researcher's chance of being an inventor on a patent in a given year. This is economically large because the base chance of a granted patent in our sample is high compared

[23]We identify research-intensive institutions as those with the "R1" Carnegie Classification, which includes about 130 universities.

[24]See this NSF example.

[25]The results are similar using the log of one plus number of patents as well.

to the chances of ever even applying for a patent in the overall U.S. population. The average chance of a researcher in our sample being an inventor on a *granted* patent in a given year is 0.23%. Bell et al. (2019) calculate that the chance of an individual *ever applying* for a patent in the U.S. population overall is 0.21%.[26] Bell et al. (2019) point out that applying for a patent is a compelling outcome to study because, despite being rare, it is important for economic growth.

Figure 5 reports the event study estimates for the patent outcomes. These indicate no pre-trends and show marked increases that start in the second year after the cut and endure for at least five years. Note that we use the patent application date, so this timing does not reflect the lags inherent in the patent grant process. However, the timing does suggest that it takes a couple of years for research funding to translate into differences in patentable outputs, which is consistent with patenting lags in other contexts, including the lag between obtaining a contract from the U.S. government and patents in De Rassenfosse et al. (2019). In Section 4, we argue that different preferences for appropriating research outputs across funding sources can offer one explanation for why we see a decline in entrepreneurship but an increase in patenting after negative federal funding shocks.

The third outcome is publication activity, which is the primary mechanism for disseminating academic research. Information in an academic publication can be freely used for follow-on innovation; this openness contrasts with the outcomes of high-tech entrepreneurship and patenting, which represent forms of rivalrous, private commercialization. Table 2 column 6 indicates that the large, negative shocks to federal funding reduce a researcher's overall number of publications by about 15% from the mean. The event studies on the number of publications (Panel B) and any publications (Panel A), in Appendix Figure A.5, suggest a negative effect starting in the second or third year after the funding cut. However, this figure is much noisier than the other two outcomes, suggesting caution in interpreting the average negative estimate. Below, we show that there are more compelling declines in certain types of publications.

How large are these effects economically? In a simple back-of-the-envelope calculation, we find that if our results were to generalize to all university researchers, then they would imply that the average shock (from our data) would lead to around 1,000 fewer high-tech startups in that

[26] This is from their inter-generational sample of United States citizens born in 1980–1984 matched to their parents in the tax data and linked to patent applications. They have 34,973 inventors and 16,360,910 non-inventors (Table 1 of their paper). Between 2000 and 2019, 45% of annual patent applications were granted, so presumably the share of people with granted patents is lower. See USPTO Statistics.

year from university researchers in the U.S., which is 2.4% of the total average number of annual new high-tech startups in the U.S. during our sample period. The analogous calculation implies 2,200 more patents (1% of the U.S. mean), and 27,000 fewer publications (4% of the U.S. mean in the PubMed universe). Of course, this sort of extrapolation must be interpreted with caution, as we cannot establish external validity outside of our sample. Nonetheless, this exercise sheds some light on the economic importance of the results.[27]

3.2 Effects by Occupation

Our data include four types of researchers: faculty, graduate students and post-docs, undergraduate students, and staff. To assess which career stage drives our results, we divide the sample to estimate our main model separately for each occupation in Table 3. Panel A shows that the negative effect on high-tech entrepreneurship appears for all four groups but is only statistically significant for graduate students and post-docs (column 2). This group has the highest propensity for high-tech entrepreneurship, 0.25%, as these researchers possess the skills and experience needed to found a high-tech startup but do not have stable academic employment (unlike most faculty). It makes sense that they would be most sensitive to funding changes, as they are dependent on grant funding to support continued academic work.

We next consider patents in Table 3 Panel B. The positive average effect is driven by faculty and graduate students/post-docs (columns 1-2), which is intuitive because other groups are unlikely to be inventors on patents in general. Again, the effect is significant only for graduate students, though its magnitude is also large among faculty, where the lack of significance may reflect a relatively small sample.

Third, we consider publications in Panel C. Here, the average negative effect is unequivocally driven by faculty, where we see a strong, negative effect. This also accords with intuition since faculty have stable academic careers in which they will author many academic papers, whereas other researchers are, even absent funding shocks, likely to move on to other careers. Thus,

[27] External validity is problematic for at least two reasons. First, our sample contains only top-tier research universities. Second, our results are based on individuals who happen to experience large and temporary federal funding declines within their narrow field of study during our sample period. The calculations are as follows. In the 22 universities covered by the UMETRICS data, there are approximately 86,000 university researchers per year. These 22 universities account for about 15% of total federal funding to all US universities (according to NSF IPEDS data). We estimate (0.0018*86,000)/0.15 = 1,032 fewer high-tech startups, (0.0039*86,000)/0.15 = 2,236 additional patents, and (0.0466*86,000)/0.15 = 26,717 fewer publications.

while graduate students and post-docs drive outcomes related to private sector employment, this measures the long-run effects on an academics research program. Although the publication result is driven by faculty, this does not divorce it from our larger analysis. Publications are crucial means by which knowledge is disseminated, and this effect reflects a decrease in openly available scientific knowledge. Without all three outcomes, we would not have a complete picture of research innovation output.

Overall, we find no effects among staff. Including staff as an occupational category provides a useful placebo group because we do not expect them to determine the direction of research and trajectory of output commercialization or dissemination. Their outputs could, however, be impacted by funding levels through other channels, so we include them in our main analysis.[28]

3.3 Heterogeneity in Patent and Publication Effects

Patents and publications vary widely in their quality and importance to future research.[29] By exploring heterogeneity in their characteristics, we can begin to shed light on the mechanisms for the average effects. We consider three dimensions related to knowledge spillovers and appropriation.

We first split the sample around the median by generality, which measures the breadth of future patent citations across classes. Figure 6 Panels A and B use the event study specification (Equation 2) and suggest a stronger effect for low-generality patents.[30] The regression results, in Table 4 columns 1 and 2, are consistent with these event-study analyses. Second, we consider citations, which measure impact on future innovation and, thus, are a proxy for knowledge spillovers. Figure 6 Panels C and D show that the average effect is largely driven by low-citation patents. Columns 3 and 4 of Table 4 confirm that the coefficient is larger for patents with below-median citations.

Column 5 of Table 4 shows that there is a large positive effect of the federal funding cuts (more than twice the mean) on the chances of having a patent assigned to a private firm, rather than to the researcher or university. When matching assignee names to funder names, we find

[28] In unreported analysis, we examined effects by field, and found them to be driven across all outcomes by the hard sciences, such as engineering and biomedical research, rather than by the humanities.

[29] Clearly, high-tech startups also vary in their quality. Unfortunately, the Census disclosure policies constrain us in splitting the sample by startup growth characteristics.

[30] We also considered originality but did not find significant heterogeneity.

that over 40% of patents with private sector assignees are assigned to a company funding the research. This may reflect a private funder licensing the patent. In sum, the positive effect of negative federal funding shocks on patent activity does not seem to reflect additional research that is particularly impactful, but instead leads to more incremental patents that are much more likely to be appropriated by private firms.

We turn to publication heterogeneity in Table 5. First, we divide the articles around the median impact factor of their journals. A journal with a high impact factor is relatively more important to the field and generally contains higher-quality articles. The negative effect on publications is clearly driven by a decline in publications in high-impact journals (columns 1 and 2). This variation is also apparent in the event study design reported in Figure 7 Panels A and B. While the overall event study for publications is noisy, Panel B shows clear evidence for a decline in high-impact journal publication beginning in the second year after the shock and staying persistently lower after that. Next, we turn to whether the publication itself has above- or below-median cites from future publications. As with patents, this provides a measure of knowledge spillovers and importance. We find that the decline is mostly driven by high-cite publications (Table 5 column 4). This is again visible in the figure, where there is no measurable effect for low-cite publications, but a noticeable discontinuity for high-cite publications (Figure 7 Panels C and D).

The third characteristic is whether the content of the publication represents basic or applied research. We find that the decline is driven by basic publications and that, in fact, there is an increase in publications that are cited by subsequent patents. Specifically, we split the sample on the Ke (2019) score, based on terms related to clinical research, in Table 5 columns 5-6. The results show that the negative federal funding shocks reduce the number of basic publications by 0.022, which is 26% of the mean. We consider a second measure, derived from "Reliance on Science" data developed by Marx and Fuegi (2020), which is whether the publication is cited by any patents, in column 7. The shocks increase the number of publications cited by patents by 0.012, which is 29% of the mean. This is consistent with a decrease in basic research, which is less likely to be cited by patents.

Overall, this evidence about which types of publications and patents drive the main effects suggest that the negative shocks to federal funding lead to substitution away from more open research with greater impact on future knowledge, and towards more subsequently appropriated research.

3.4 Robustness Tests

In this section, we conduct supplementary analyses to test our main identification assumption and ensure that our specification and data construction decisions do not spuriously explain the findings.

Technological Opportunities. A key threat to identification is that the large shocks we employ may reflect fundamental long-run changes in technological opportunities in the affected fields. Three points raised already speak directly against this concern. First, the shocks are mean-reverting, and therefore do not reflect long-term technological opportunities. Second, in the context of our results, if federal funding cuts are a response to technological opportunities, we should see some response in innovation outcomes before funding cuts, which we do not find. Third, the direction of potential bias goes in the opposite direction of the effect for patents: if negative shocks reflect declining technological opportunities, then they should be associated with fewer rather than more patents. In addition to these points, we present interview and case study evidence in Appendix B.2 that the one-time negative funding shocks are typically due to a decision to increase one program's funding in a particular year, leading other programs to receive arbitrary cuts.

We next provide additional evidence that technological changes are not driving the federal funding cuts used in our main analysis. Most importantly, we conduct falsification tests where we examine whether aggregate high-tech entrepreneurship in entire industries and aggregate patenting in entire patent classes appear to respond to placebo shocks based on these one-time funding cuts. Both high-tech entrepreneurship and patenting in the broader economy are largely the product of private sector rather than university research. Thus, these aggregate outcomes should not appear to react to temporary federal funding cuts unless these cuts are themselves correlated with technological opportunities that determine economy-wide high-tech entrepreneurship and patenting. We did not conduct an analogous test for publications because most publications are produced by university researchers who are clearly directly affected by federal funding availability.

We begin with high-tech entrepreneurship. Since founding a startup in an industry should primarily be a function of market and technological opportunities, an idiosyncratic federal funding shock in a particular narrow industry should have no effect on the level of startup formation in that industry. However, if federal funding cuts are related to declining technological opportunities, we should also see a decline in aggregate high-tech entrepreneurship in related areas. We use the complete Longitudinal Business Database (LBD) from the U.S. Census Bureau to construct a balanced panel of the number of startups formed annually in 146 high-tech industries. We identify an industry as shocked in a given year if a researcher from our main sample is shocked in that year and then goes on to found a high-tech startup in that industry. Therefore, by construction, all "shocked" industries are high-tech. Control industries are those high-tech industries that are never shocked. This yields a balanced panel in which some high-tech industries receive placebo shocks in particular years.[31] Figure 8 Panel A shows the event study for the number of new high-tech startups, using the same model as Equation 2 while controlling for industry and year fixed effects. The figure indicates no pre-trends and no change post-shock, with 95% confidence bounds well outside those of our main effect, supporting the assumption that the shocks are idiosyncratic.

Using the same intuition, we next turn to the number of patents. Most patents in a given patent class are produced by inventors in the private sector who do not depend on federal funding, so a one-time federal funding shock should not affect patents in that class unless the shock is correlated with contemporaneous technology shocks. We map CFDA codes one-to-one to patent classes. For each patent class, the corresponding CFDA code is the most common main CFDA code of researchers with patents in that patent class.[32] We then repeat the event study at the patent class-year level, where a treated patent class is shocked if its corresponding CFDA code is shocked. Figure 8 Panel B again shows no evidence of a pre-trend or post-shock positive effects. In sum, this analysis offers evidence that our main results do not reflect technological changes or opportunities associated with a CFDA program's field.

[31]The LBD includes all non-farm, private business activity. We define industry as a 6-digit NAICS code, which is quite granular (there are approximately 1,000 codes in total, and 146 high-tech codes; examples include "Glass and Glass Product Manufacturing" and "Satellite Telecommunications"). We compute the number of startups in each industry-year. The mean number of high tech age zero firms in the BDS 2001-2017 is 42,833 and the mean number of total high tech firms in these years is 409,461, or a ratio of 0.1046.

[32]For example, suppose 50 researchers have patents in a patent class, and among those researchers 20 of have a main CFDA code A, 15 of them have main CFDA code B, and 15 have other CFDA codes. Then the CFDA code for that patent class is A. Note the "main CFDA code" is the CFDA code with most funding. We do not include the 20 patent classes where no UMETRICS inventor has a patent, and we exclude patents of UMTERICS inventors in this analysis to avoid mechanical effects.

Exposure by Grant Timing. If the channel connecting aggregate funding with individual research outcomes is in fact individual access to federal funding, then we expect that individuals who recently obtained a grant will be less exposed to funding shocks than those whose grants are closer to renewal or end-of-life, because most grants expire after three to seven years. To test this hypothesis, we conduct a heterogeneity analysis based on whether the previous grant was awarded recently (<2 years ago vs. >=2 years ago).[33] The results are in Table 6. Column 1 shows that the shocks reduce federal expenditure by more than twice as much among the group with older awards, consistent with them being more likely to need to acquire or renew funding that year. Column 2 shows that the effect on high-tech entrepreneurship is small and statistically insignificant for researchers with recent funding. It is 50% larger and significant at the 1% level for researchers who likely need new funding. Columns 3–4 show that the effects on patents are entirely driven by this group with older federal awards; in contrast, the coefficients are near-zero and insignificant for the group with more recent awards. Columns 5–6 show that the effects on publications are also larger among researchers without recent federal awards. The differences are statistically significant at 10% level except for publications. These results offer further confirmation of our identification approach.

Positive Funding Shocks. We focus on negative rather than positive shocks because they are more policy relevant given the secular decline in federal funding at the aggregate level. In a supplementary test, we examine whether large and temporary positive shocks have symmetric effects. Similar to the negative shocks, we identify positive shocks that meet the following conditions: (1) the total amount of federal funding in the field increases by at least 40% from the previous year; (2) the increase in funding is temporary and the funding level reverts back to the pre-shock level at some later point in time; (3) there are no large positive or negative funding changes (>20% or <-20%) in the two years preceding the shock. There are 27 positive shocks that satisfy these criteria. Table A.3 shows that following positive shocks in a field, researchers in that field have higher federal funding and more publications, but fewer patents and less high-tech entrepreneurship. The effects are noisier than for the negative shocks due to the small number of

[33]For each award, the first year of the award is the first year with any positive expenditure. For each person in each year, we take the average age across federal awards with positive expenditure so that the age of the award is the current year less the first year of the award. If there is no positive expenditure, we impute the average age as last year's average age plus one. The median average award age is two years at the time of the shock among treated individuals. Therefore, our split is around the individual-level median.

positive shocks, but have opposite signs and similar magnitudes as our baseline negative shocks in Appendix Table 2. This indicates that the effects of changes to federal funding are at least weakly symmetrical for positive shocks.

Lab-Level Analysis. Funding shocks not only affect individual researchers' innovation outcomes, but may also affect researchers' entry to and exit from research labs as well as lab-level outcomes. For example, if a lab does research in a field which has a large and temporary negative federal funding shock, researchers in that lab may leave, which could impact the lab's innovation outcomes at the extensive margin. In order to assess these possibilities, we define a lab as a team of researchers working under a common principal investigator (PI) in a given year. A lab is treated if all researchers of the lab are in the treated group in the year before the shock.[34]

The lab-level results are largely consistent with the main analysis. The results are reported in Appendix Table A.4. Following a negative shock to federal funding, the number of researchers in a lab declines by 0.4 on average (column 1). As in the main results, we find negative effects on federal funding, high-tech entrepreneurship and publications of affected labs but positive effects on patents (columns 2–8). They are less precise because the lab aggregates all researcher types and has a much smaller sample size. However, they capture the total effect on the innovation outcomes at the lab level, incorporating both changes in innovation outcomes of individuals within the lab on the intensive margin and changes due to the entry and exit of researchers on the extensive margin.

Standard Error Assumptions. Our main results cluster standard errors at the individual level because each person's treatment status is based on whether she gets the majority of funding from treated or control CFDA codes. We also show that our results are robust to alternative standard error clustering. First, in Appendix Table A.5, we report our main results with standard errors clustered at the level of the university department to address concerns that researchers in the same university and department might experience correlated shocks to federal funding. Second, in Appendix Table A.6, we cluster at the level of the researcher's main CFDA

[34]We dropped 2% of labs with both researchers in the treated group and researchers in the control group in a given year. We also dropped less than 0.1% of labs with over 100 researchers whose PIs may be incorrectly imputed.

code, which is the CFDA code from which the researcher receives the most funding, to address correlation within the aggregate narrow field. The effects on individual funding (column 1), high-tech entrepreneurship (column 2) and patenting (columns 3-4) are robust to both approaches. However, the effect on publications becomes insignificant. In unreported tests, the strong negative effects from Table 5 on high-impact journal, high-citation, and basic publications are robust to both alternative clustering approaches.

4 Mechanisms

In this section, we examine why cuts to aggregate federal funding impact the research outputs of individual researchers. Two possibilities are that these cuts (1) lower the *level* of a researcher's funding; and (2) alter the *composition* of a researcher's funding, i.e., whether the funding is from the federal government, private firms, or other sources. We begin to assess these in Table 7. In column 1, we find that federal funding cuts reduce researchers' overall funding by 14%, which is smaller than the effect on federal funding from column 1 of Table 2, suggesting that researchers substitute federal with non-federal sources of funding after experiencing a negative shock to their federal funding.[35] We next examine how the federal funding cuts affect researchers' funding from private firms. Column 2 of Table 7 shows that private funding increases by 15% following these shocks, though this is not statistically significant. However, when we restrict to researchers in fields that get at least some private funding in column 3, we find a larger and statistically significant increase of 29%.[36] This suggests that researchers compensate for declines in federal funding by seeking more private funding.[37]

If such compositional changes away from federal and towards private funding are important, we expect that the negative federal funding shocks should push researchers toward lower reliance on federal funding and greater reliance on private funding as a share of total funding. In Figure 9, we plot the event studies for the shares of federal and private funding around the negative

[35] Appendix Table A.4 shows a similar finding at the lab-level. Federal funding falls by 23% (column 2). There is a smaller, insignificant effect on total funding (column 3).

[36] We restrict to university-by-field combinations with an above-median average share private funding (the median university-field has zero private funding share).

[37] In unreported results, we find that changes in funding in other sources (not federal or private) is negative, economically small, and insignificant, suggesting that researchers do not compensate for the decline in federal funding by getting funding from the sources outside of private sector.

federal funding cuts. We see no pre-trend and then a significant decline in the federal share over a three-year period after the cut, leveling out subsequently (Panel A). The inverse pattern appears for the private share (Panel B). Table 7 presents the differences-in-differences estimates, which similarly show a negative effect of the shocks on the share of federal funding (column 4) and a positive effect on the share of private funding (column 5). The increase in the share of private funding is close in magnitude to the decline in the share of federal funding.

In sum, the evidence supports the conclusion that changes to researchers' overall funding levels and composition of funding play a role in explaining the effects of federal funding cuts on research outputs. We next propose three non-mutually exclusive channels through which the level and the source of funds could affect research output. First, the decline in the overall level of researchers' funding could have a direct first-order effect on researchers' productivity as less resources are available to conduct research and innovation. Second, the decline in federal funding could affect the direction of research as federal funders may be more willing to fund basic research than other sources. Finally, an increased reliance on private funding could lead to changes in the nature of appropriation of research: private industry funders may seek to appropriate research outputs, leading to research more often commercialized by the funder.

To explore these channels, we begin with descriptive evidence that federal and private funding awards have different characteristics and are associated with differing research outcomes. We present these statistics in Table 8. For this exercise, we use the whole sample of UMETRICS university researchers (beyond the regression sample) to provide a complete picture of the differences between federal and private grants.[38] Consistent with the productivity channel, federal grants tend to have larger amounts of funding, larger team sizes, and more, and more highly cited, patents and publications. Consistent with federal funders producing more basic research, on average patents funded by federal grants are more general, and federally funded publications are more basic. Finally, consistent with the appropriation channel, patents funded by federal grants tend to be less likely to be assigned to a private firm than patents funded by private grants; and patents and publications funded by federal grants tend to be more

[38]In Table 8, we do not include Census outcomes due to constraints with the disclosure process. The calculations are as follows. The number of employees, total funding, grant duration, and team size are calculated from grant-level data. Team size is defined as the total number of researchers receiving a positive amount of funding from a grant. Patent (or publication) outcomes are calculated from patent (or publication) level data and a patent (or publication) is federally funded if the authors get the majority of their funding from federal sources before the patent application date (or publication date).

highly cited. Thus, at a purely descriptive level, it appears that all three channels may help determine research output.

We next examine how our main results on the effects of federal funding cuts on patents, publications, and high-tech entrepreneurship align with these three channels.

Research Productivity. Since the aggregate negative funding shocks reduce researchers' total funding and lab sizes, their aban impair their abilityIt is possible that our main results reflect a decline in research productivity due to the the loss of resources coming from the overall decline in the level of a researcher's funding. Research funding is crucial for the acquisition of inputs to the research process: necessary equipment, information technology, qualified personnel, and travel to conferences, among many other necessary purchases. to conduct research.

If research funding increases research productivity in the sense of leading to more total research output, we would expect researchers with more research funding to produce (a) more patents, (b) more high-tech entrepreneurship, and (c) more publications. However, in our main analysis, we instead find that, while negative shocks to federal funding reduce high-tech startup formation and publications, they increase patenting. This points to a more nuanced perspective than research funding cuts simply decreasing researcher productivity along all dimensions.

Basic vs. Applied Research. A second possibility is that the federal government may prefer to fund more basic research, while private funders may prefer to fund more applied work, and each may push researchers in one direction or the other once the funding relationship is established. Above, we argued that federal grants are important for basic publications because they increase the researcher's overall level of funding. Although support for basic science has long been an argument for federal research funding, federally funded research is not, in practice, necessarily more basic: the share of funding supporting basic research is essentially the same across federal and non-federal funding sources (NSF 2018), partly because private funders often fund research in "Pasteur's quadrant," namely basic research but directed at real-world challenges or problems (Atkinson 2018).

If federal funding pushes researchers toward doing more basic research, we expect that more federal funding should yield fewer patents and less high-tech entrepreneurship among university researchers, as both of these outcomes are relevant only to commercially applicable research outputs. More federal funding should also lead to more original and general patents, which cite or are cited by a broad array of fields, as well as more basic publications. Our results on patenting and publications are generally consistent with these predictions; federal funding cuts increase patenting and reduce basic publications and the generality of patents, although we do not find any effects on patent originality (unreported).

However, the negative effect of the funding cuts on high-tech entrepreneurship contradicts this channel, because high-tech entrepreneurship clearly requires an applied idea.[39] Consider the example of the $11 million in grant funds from the U.S. Department of Energy that MIT Professor Donald Sadoway and his PhD student David Bradwell used to develop a molten metal battery for large-scale grid energy storage. The team chose to bring the battery to market via a startup named Ambri. Bradwell served as co-founder, while Sadoway remained a full-time professor at MIT.[40] With a clear applied intention, the federal grant described the researchers as "creating a community-scale electricity storage device using new materials and a battery design inspired by the aluminum production process known as smelting."[41]

In sum, federal funding pushes researchers to do more basic science, which may account for some of the effects on patenting and publications, but it does not explain the results on high-tech entrepreneurship and is unlikely to be the only mechanism for our findings.

Appropriation of Research. Finally, the effects of federal funding cuts on innovation patterns may reflect the shift in researchers' funding composition away from federal and towards private sources, which have fundamentally different objectives. Industry funders seek private benefits and therefore have an incentive to appropriate research outputs. This leads them to demand ownership rights, accomplished via detailed legal contracts governing intellectual property and disclosure of sponsored university research. In contrast, the federal government invests in research to produce socially valuable goods, including training future academics, and thus aims to fund innovation and research that is more widely accessible.[42] Hence, privately funded research might result in research outputs that are more often appropriated by the funder,

[39] A factor that is also relevant to the effect of federal funding on high-tech entrepreneurship is the increased focus of universities on commercialization. Following the Bayh-Dole Act of 1980, it became much easier to commercialize inventions that have government financial support (Henderson, Jaffe and Trajtenberg 1998, Mowery, Sampat and Ziedonis 2002, Hausman 2017). This could have shifted all research in a more applied direction, regardless of funding source.

[40] See Ambri website and MIT news.

[41] See DOE Grant Page.

[42] Technical march-in rights, which allow a federal funding agency to disregard a patent's exclusivity, are typically never exercised.

while federally-funded research outputs may be more open and more easily appropriated by the researchers—either to benefit their own startups or to be placed in the scientific commons via publications.

This hypothesis yields three predictions: (a) federal funding should yield fewer patents, which are important for appropriation by the private sector; (b) federal funding should yield more high-tech entrepreneurship among university researchers (who are free to use the IP for the benefit of their companies); and c) federal funding should yield more publications, which are a measure of publicly disseminated research outputs (which is arguably their key attribute as compared to patents).

Our results line up with all these predictions. Regarding (a), there is a strong positive effect of the federal funding cuts on patenting. The cuts also increase the probability that a patent has a private assignee, consistent with appropriation by the funder. In manually matching private funders to patent assignee firms, we find that 40% of the privately assigned patents are assigned to the firm that funded the researcher's grant. This statistic is much larger than the 1.6% that would be predicted by random chance (one divided by the number of corporate patent assignees that fund university researchers in our data). Regarding (b) and (c), the funding cuts have strong negative effects on high-tech entrepreneurship and publications. As federal funding has fewer strings attached, the IP it funds is freer to be used in publications and startups. For example, Sergey Brin and Larry Page created the PageRank algorithm while they were PhD students at Stanford as part of their work on a grant from three federal agencies to develop a "Digital Library."[43] They were able to make this algorithm the basis for their startup, Google, in part because the government did not assert rights to the output. Had a private company funded the research, where and how this innovation would have been commercialized might have been quite different.

The other career results are also consistent with the appropriation channel. There is a negative effect of the federal funding shocks on the chances of staying employed at the university. Furthermore, we find descriptive evidence that human capital created by a private grant is often appropriated by the sponsor. Among individuals with private funding who subsequently work at any funder firm (~500 firms), 20% go to the firm that funded their own research. This aligns with a common perception that firms sponsor academic research in part to

[43] See here and here.

train future employees.

In practice, the contracts between funders and universities support of an appropriation mechanism. Private funders negotiate with universities over ownership of research results. In contrast, federal grants come without these negotiations or contracts and offer the university and its researchers free use of any outputs. The Stanford University Industrial Contracts Office emphasizes in its guide to university researchers that industry funders approach research in a "closed" manner, while the standard at the university is to be "open" and "public."[44] To explore this further, we reviewed actual industry-university contracts. One example of a contract between NYU Langone Health (the Grossman School of Medicine) and a redacted industry funder is provided in full in Appendix D, with key components highlighted. The contract claims broad intellectual property rights for the funder:

> "7.2(b) Results. Company shall have and retain all right, title and interest in and to the Results, and Institution hereby assigns to Company all of its right, title and interest in and to the Results. All information regarding the Results shall be Confidential Information of the Company. Company hereby grants to the Institution a limited, non-exclusive, and fully-paid license to use the Results for its internal academic, research and educational purposes....
>
> 7.2(e) Joint Inventions. Institution and Company shall jointly own all right, title and interest in and to all Joint Inventions other than Company Technology Inventions ("Jointly-Owned Joint Inventions"). To the extent permitted by law and any conflicting obligations, Institution hereby grants to the Company an exclusive option to obtain an exclusive license to and under Institution's rights, title and interest in and to such Jointly-Owned Joint Inventions for all purposes on commercially reasonable terms to be negotiated by the parties in good faith."

These paragraphs highlight how the contract assigns commercialization rights to the company funding the research. The contract also restricts researchers from disclosing confidential information without the company's explicit approval (see paragraph 6.2).

We reviewed contracts from a variety of research universities, some of which provide template agreements on their industry contracts office websites. In our conversations with contract officers, they emphasized that these tend to be a starting point for negotiations, with the

[44] See Stanford contracts website.

firm typically imposing more stringent requirements.[45] Harvard University's standard contracts with industry, even before negotiations and for patents that Harvard has claimed for itself, states that: "With respect to each Invention, Harvard hereby grants to Company an option to negotiate in good faith with Harvard (an "Option") for a non-exclusive or an exclusive (at Company's discretion), royalty-bearing, worldwide license..." Similarly, the University of Maryland's standard contract notes that the sponsor will be notified of any research results within 60 days and may choose "to negotiate an exclusive or nonexclusive commercial use license in the UMD Research Results." Notably, the research results subject to these contracts are potentially very broad, including "all data, inventions, discoveries, copyrightable works, software, tangible materials, and information that are conceived of, first reduced to practice, collected, or created in the performance of the Research Project and funded under this Agreement." The contract template further states that "UMD and Sponsor will jointly own all rights, title to and interests in Joint Research Results," which include anything making use of the sponsor's material.

In sum, it is clear from the contracts themselves—especially when compared with the absence of any contract for federal grants—that appropriation of research output is a key rationale for private grants to university researchers. Our results suggest that a shift away from federal funds and towards private funds yields IP and human capital that are more often appropriated by the private sponsors and less often deployed in high-tech startups. However, it is important to caveat that multiple mechanisms could be at work to explain the effects we document.

5 Concluding Discussion

The decline in federal government funding as a share of U.S. university research expenditure has raised concerns among practitioners (Holt 2016). Observers point to anecdotal evidence that applied but transformational inventions often originate in federally-funded university research, such as the internet and artificial intelligence, as well as companies such as Google and Genentech.[46] There is concern that these types of inventions require the openness of federal funding; for example, in 2017, an *Atlantic* magazine article argued that academics are "under

[45]These negotiations can be complicated. One scientist consulted by the authors recalled that a contact between U Mass Boston and Wayfair took a full year to negotiate.

[46]Google: NSF; see here. Genentech: NIH; see here.

increased pressure from corporate funders to agree to conduct studies that would remain the property of the funder" (McCluskey 2017). However, there is little rigorous evidence on the importance of federal funding for academic research outputs.

We shed light on this question using individual data on grant employees from 22 universities linked to patents, publications, and U.S. Census Bureau data. To identify the causal effect of federal funding, we use large, negative, idiosyncratic shocks to aggregate federal funding in a researcher's narrow area of study. We find that these cuts to federal funding increase patenting, but reduce high-tech entrepreneurship and publications. We show that the additional patents are relatively low-quality, and the lost publications are relatively basic as opposed to applied. These results demonstrate an important role for federal funding in a range of innovation outcomes.

Next, we examine mechanisms. The federal cuts lead to declines in the overall amount of researcher funding as well as a change in composition away from federal and towards private funding. We propose three non-mutually exclusive channels through which the level and the source of funds could affect research output. Our evidence is most consistent with a channel where a shift from federal to private funding affects researchers' objectives and constraints due to changes in contractual and incentive structures (Azoulay and Li 2020). While federal awards typically assert no property rights to research outcomes, private firms have incentives to appropriate research outputs and, for that reason, employ complex legal contracts with researchers. Our results, together with evidence from industry contracts, suggest that private funding can lead to greater appropriation of IP by the sponsoring firms.

Our results are relevant for policy. They point to an important role for federal funding in generating research that is more open and has large knowledge spillovers. Our findings also relate to the increasing dependence of universities on industry funding, with many actively recruiting corporate research sponsors.[47] These efforts to compensate for declining federal funding with more corporate funding may lead to fewer knowledge spillovers. This relates to an inherent tension that emerges when private firms benefit from funding university research. A key rationale for government subsidy of science is that private firms cannot fully appropriate research outcomes and therefore underinvest (Nelson 1959, Arrow 1962). To the degree that academia is a second-best solution to this underinvestment problem, greater appropriability and

[47]For example, a research program at Virginia Tech notes on its website that becoming an industry affiliate of the program "is an excellent way to get broad access to MICS's research and intellectual property (IP) and to direct the focus of the MICS research." See here.

private sector funding of research in general should improve efficiency. However, if research that would otherwise be left in the public domain is now privately appropriated, it will yield fewer knowledge spillovers (Aghion et al. 2008). Our evidence supports this possibility.

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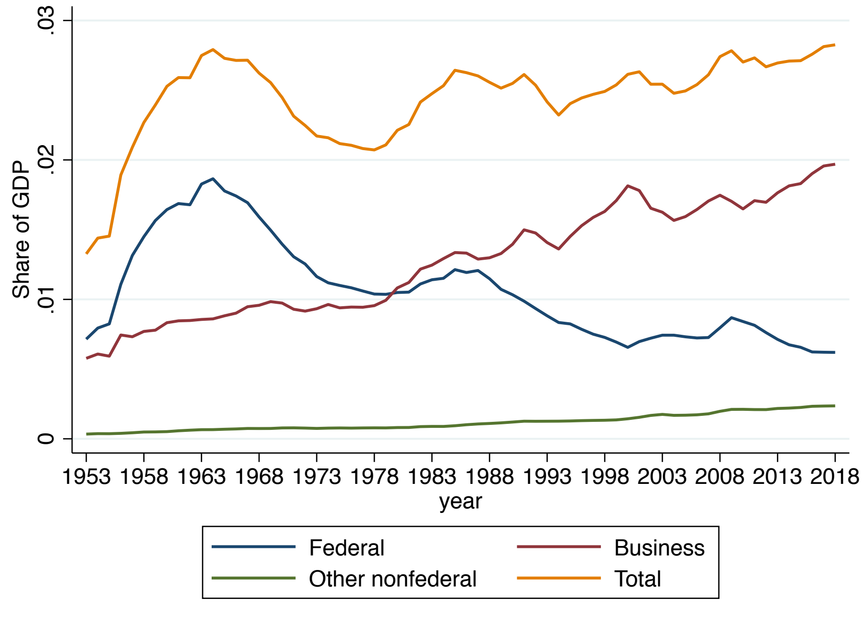
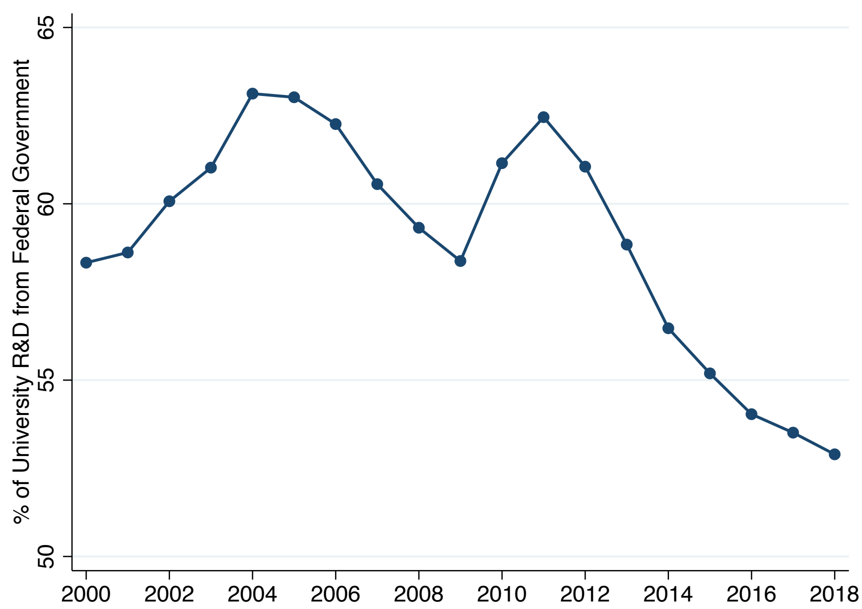
Figure 1: Sources of U.S. Research Funding, 2000-2018

Panel A. All R&D

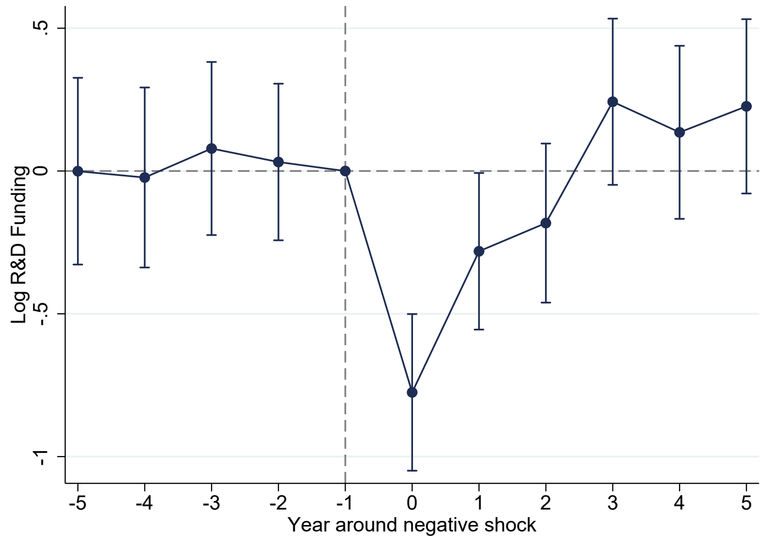


Panel B. Higher Education R&D



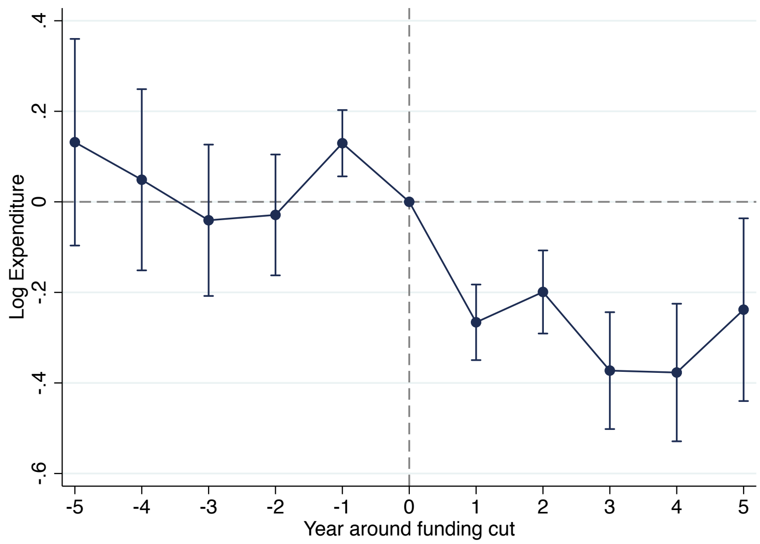
The top figure shows the percent of total U.S. R&D spending by source of funds. The bottom figure shows the share of higher education R&D expenditures funded by the federal government in each year from 2010 to 2018. Data are for all years available from the National Science Board and the NSF Higher Education Research and Development (HERD) Survey.

Figure 2: Aggregate Funding of Research Expenditure from Federal Grants around Shocks



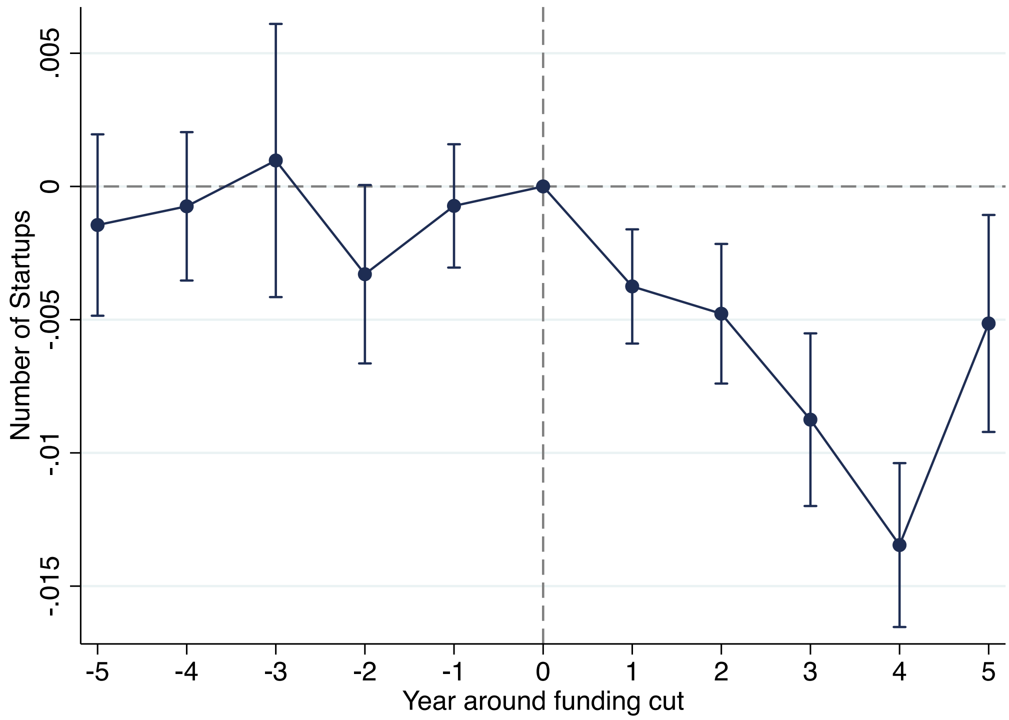
This figure shows the "first stage" results underlying the identification strategy: that large, negative shocks at the CFDA program-level are temporary and without pre-trends. We run a standard event-study regression at the CFDA level comparing the log R&D expenditure of the 61 CFDA codes with large negative shocks in each year (treated group) and not shocked CFDAs (control group) around the shock. The figure includes 95% confidence intervals.

Figure 3: Individual Funding of Research Expenditure from Federal Grants around Shocks



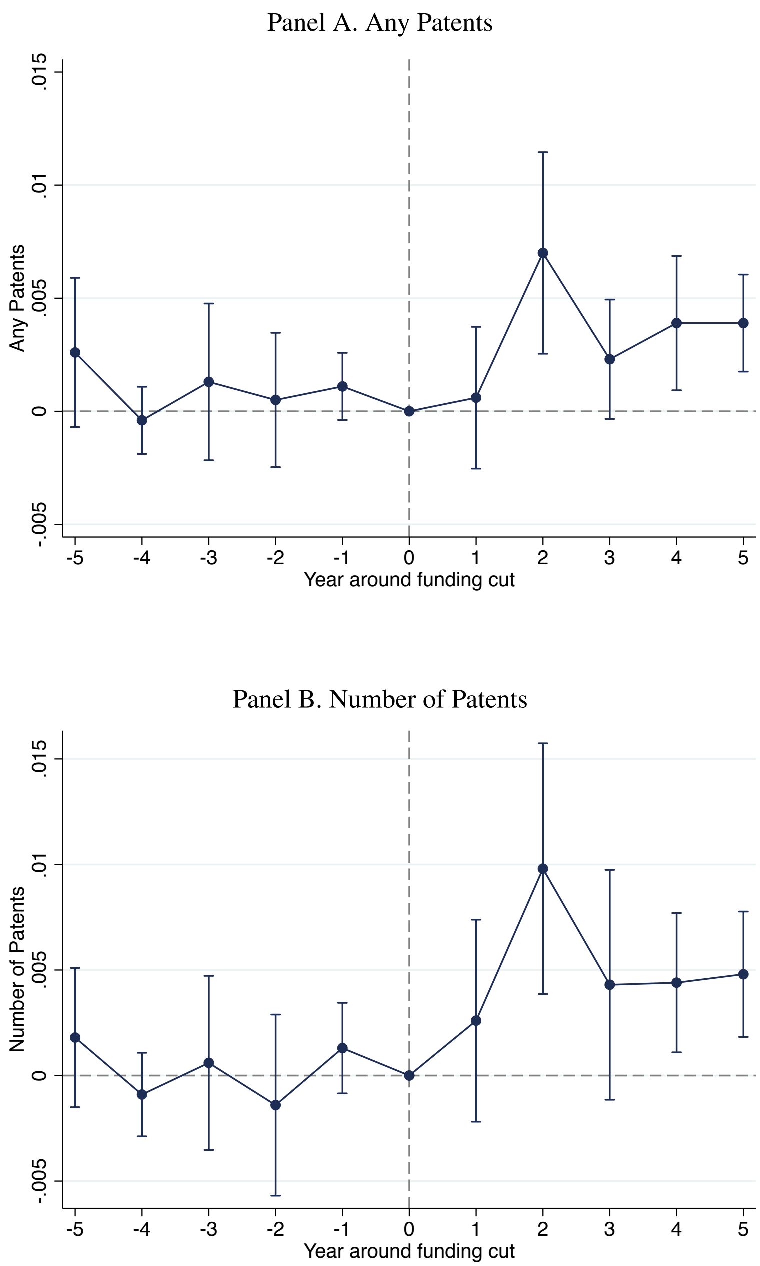
This figure shows that large, negative shocks at the CFDA program-level yield persistent declines for an individual researcher (who previously relied on funding from those CFDA codes) in their funding expenditure of federal grant money. We estimate Equation 2 and plot the event-study coefficients, where the dependent variable is the individual's (log) funding expenditure of federal R&D grant funds around the large, negative shocks at the CFDA program-level. The figure includes 95% confidence intervals.

Figure 4: Effect of Federal Funding Shocks on High-Tech Entrepreneurship



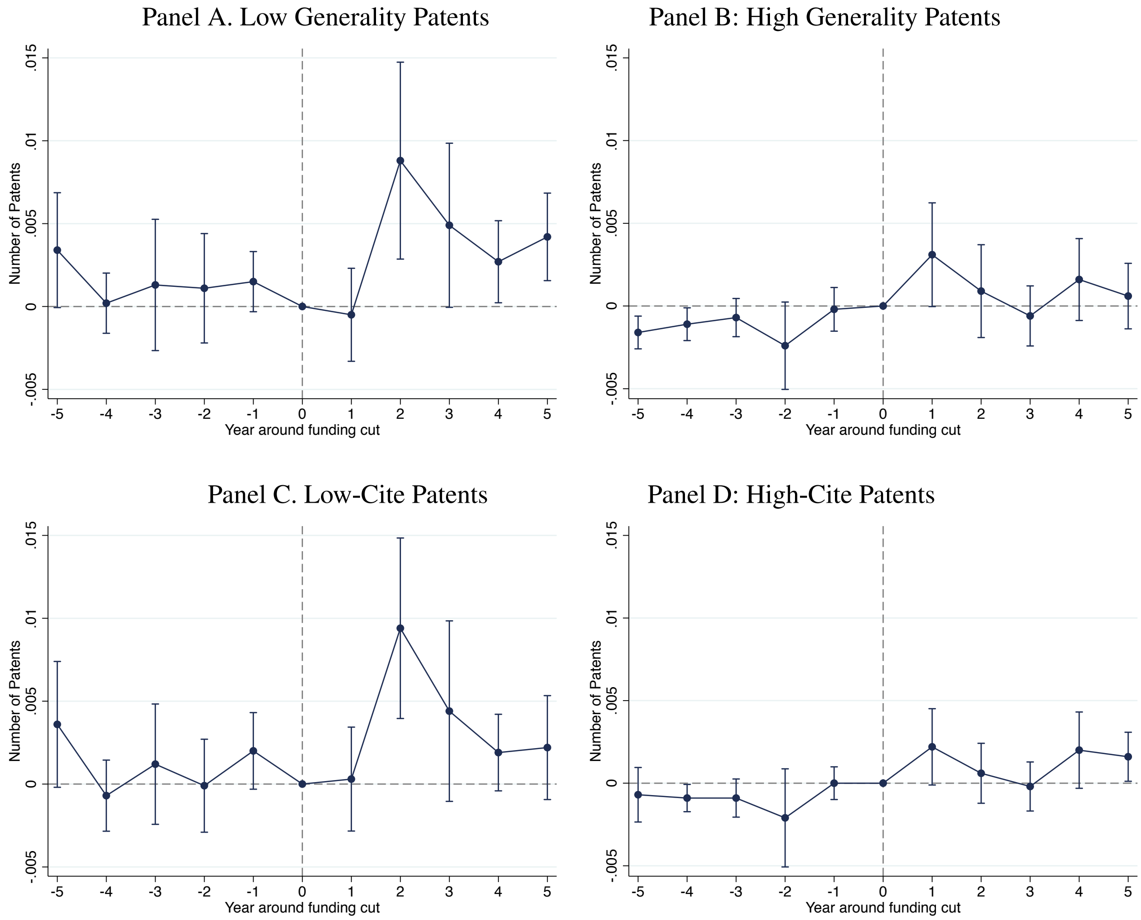
This figure shows estimates of Equation 2, describing the effect of large, negative federal funding shocks to a researcher's primary field of study on individual outcomes. In this case, the dependent variable is a measure of high-tech entrepreneurship, defined in a continuous way in order to pass disclosure review, but delivering the same economic interpretation as the main high-tech entrepreneurship variable (measured as the number of age zero high-tech firms a person works at in a given year). Specifically, it is one over the age plus one of the youngest high-tech firms that a person worked at in a given year $\frac{1}{1+\min_J(age_{i,j,t})}$, where J is the set of high-tech firms person i works at in year t. For example, if the person worked at an age zero firm (i.e., a new firm) this takes a value of 1. The regression includes principal investigator fixed effects and university-department-year fixed effects. The figure includes 95% confidence intervals.

Figure 5: Effect of Federal Funding Shocks on Patenting



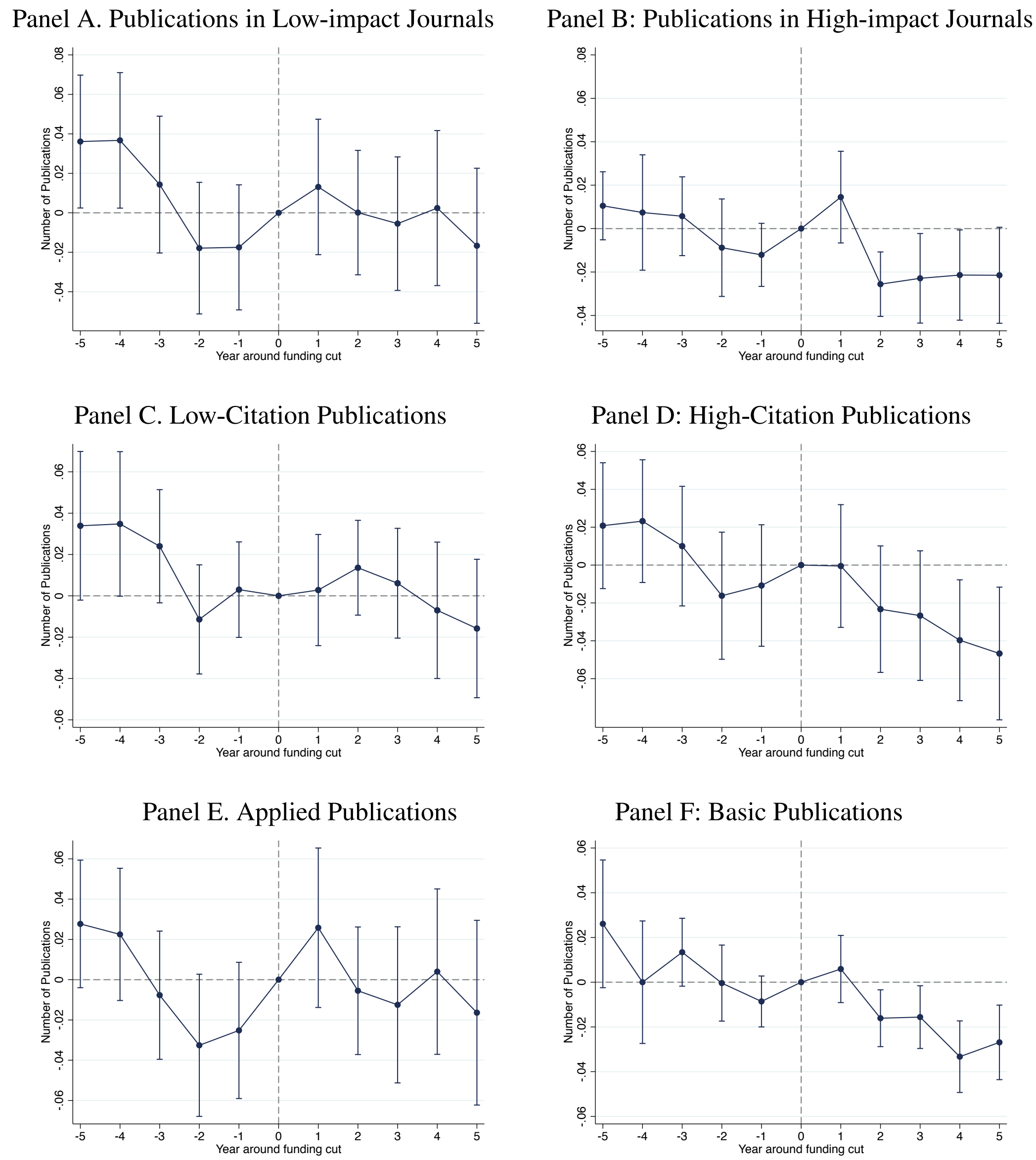
This figure shows estimates of Equation 2, describing the effect of large, negative federal funding shocks to a researcher's primary field of study on individual outcomes. In this case, the dependent variable is an indicator for having any patents (Panel A) and the continuous number of patents (Panel B). All regressions include principal investigator fixed effects and university-department-year fixed effects. The figure includes 95% confidence intervals.

Figure 6: Heterogeneity in Effect of Federal Funding Shocks on Patents



This figure shows estimates of Equation 2, describing the effect of large, negative federal funding shocks to a researcher's primary field of study on individual outcomes. In Panels A and B, the dependent variables are the number of patents that are low- and high-generality, respectively. Generality measures the breadth of patent citations across classes using information from future citations to the patent. To define "low" and "high," we split all patents in our UMETRICS-linked data around the median score for generality. In Panels B and C, the dependent variables are the number of patents that are low- and high-citation, respectively. A high-citation patent is one that future patents cite extensively, indicating it is more impactful and higher quality. Again, to define "low" and "high," we split all patents in our UMETRICS-linked data around the median number of citations. All regressions include principal investigator fixed effects and university-department-year fixed effects. The figure includes 95% confidence intervals.

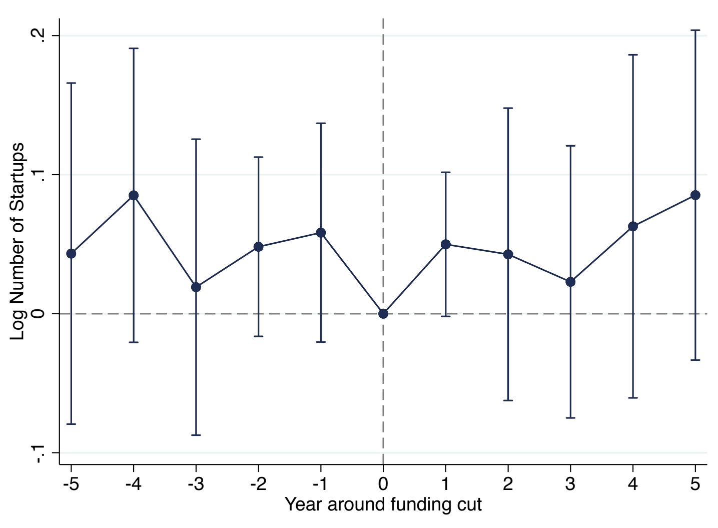
Figure 7: Heterogeneity in Effect of Federal Funding Shocks on Number of Publications



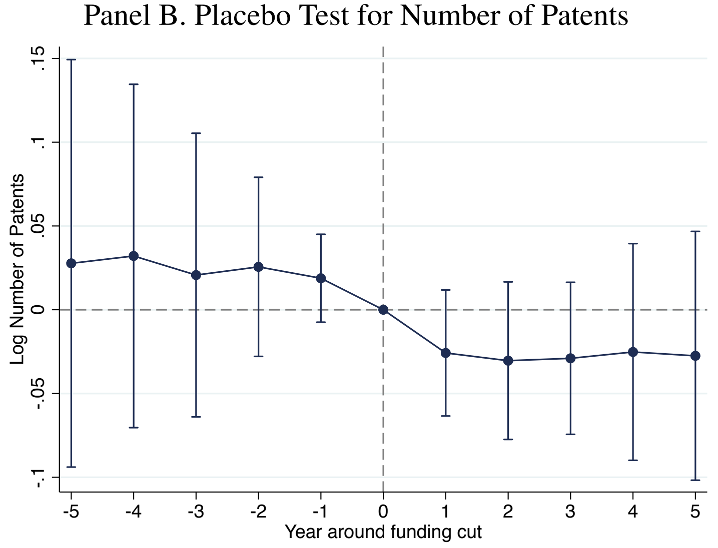
This figure shows estimates of Equation 2, describing the effect of large, negative federal funding shocks to a researcher's primary field of study on individual outcomes. We focus on heterogeneity in publications for three characteristics, in each case splitting overall UMETRICS-linked publication sample around the median. In Panels A and B, the dependent variables are the number of publications that are in low- and high-impact journals, respectively. A high-impact journal is one with a higher impact factor (i.e., greater importance) as classified by Microsoft Academic Graph. In Panels B and C, the dependent variables are the number of publications that are low- and high-citation, respectively. A high-citation publication is one that future publications cite extensively (normalized by field and publication year), indicating it is more impactful and higher quality. In Panels E and F, the dependent variables are the number of publications that are applied and basic, respectively, based on their "appliedness" score using the method from Ke (2019). All regressions include person fixed effects and university-department-year fixed effects. The figure includes 95% confidence intervals.

Figure 8: Placebo Test for Association between CFDA Large Shocks and Aggregate Outcomes

Panel A. High-Tech Entrepreneurship



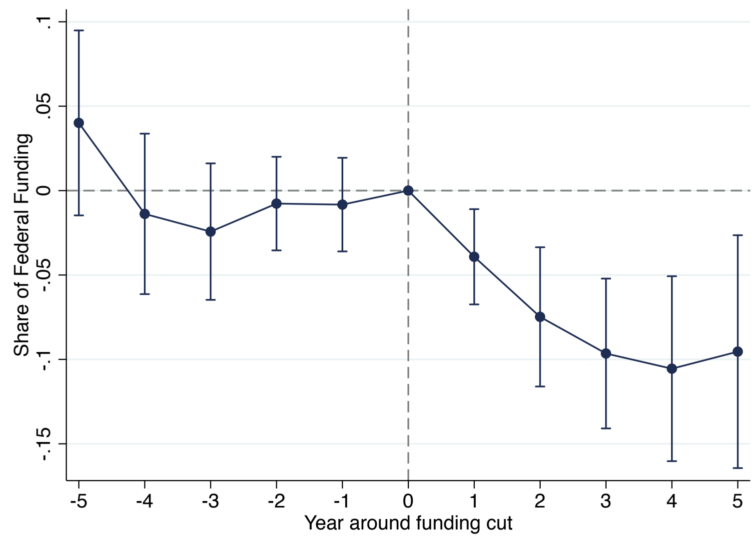
Panel B. Placebo Test for Number of Patents



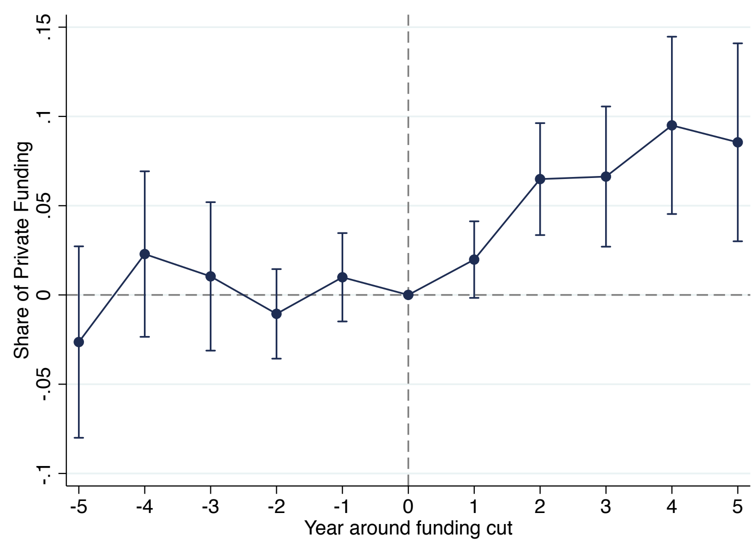
This figure shows the results of two placebo tests. Panel A shows that there is no change in the overall industry-wide log number of high-tech startups in the same 6-digit NAICS industry-years where we observe treated (hit by a federal funding cuts in in narrow CFDA programs) UMETRICS individuals to found high-tech startups after experiencing a funding shock. This model includes industry fixed effects (6-digit NAICS) and year fixed effects. Panels B conduct similar tests, showing no change in the log number of patents in treated patent technology classes. This model uses patent technology class fixed effects and year fixed effects. The figure includes 95% confidence intervals. See Section 3.4 for more details.

Figure 9: Shares of Federal and Private Funding Following Federal Funding Shocks

Panel A. Share of Federal Funding



Panel B. Share of Private Funding



This figure shows estimates of Equation 2, describing the effect of large, negative federal funding shocks to a researcher's primary field of study on individual outcomes. In this case, this figure shows the evolution of the federal and private shares of total funding following large federal funding cuts in CFDA codes. Panel A shows the share of federal funding, and Panel B shows the share of private funding. The regression includes person fixed effects and university-department-year fixed effects. The figure includes 95% confidence intervals.

Table 1: Summary Statistics

Panel A shows summary statistics for the UMETRICS sample, Panel B for the patent data and Panel C for publications data matched to the UMETRICS sample, and Panel D for the restricted-use US Census/IRS W-2 data matched to the UMETRICS sample. All four samples are person-year panels from 2001 through 2017 from 22 universities in UMETRICS data. Share Federal is the share of funding from the U.S. Federal Government. Share Private is the share of funding from the private sector (e.g., corporations or non-profits). All patent (publications) outcomes measure the number of patents (publications) that the person was an inventor of (an author of) or the number of patents (publications) of certain type. High-tech Entrepreneurship is the number of age zero high-tech firms a person works at in a given year. Entrepreneurship is the number of age zero firms a person works at in a given year (not necessarily high-tech), and Work for University is an indicator for a person working at a university.

	Number of Observations	Mean	Standard Deviation
Panel A. Umetrics			
Faculty	316,602	0.164	
Graduate Students and Postdocs	316,602	0.432	
Undergraduate Students	316,602	0.081	
Staff	316,602	0.323	
Total Direct Expenditure	316,602	13,309	96,072
Overhead Charged	316,602	3,404	13.227
Share Federal	316,602	0.801	0.365
Share Private	316,602	0.128	0.293
Share Other	316,602	0.105	0.276
Number of CFDA Codes	316,602	1.42	0.82
Δ Log(Amount R&D)	316,602	0.041	1.06
Panel B. Patents			
Any Patents	316,602	0.0023	0.048
Number of Patents	316,602	0.0028	0.067
Number of Patents with low citations	316,602	0.0019	0.048
Number of Patents with high citations	316,602	0.0009	0.041
Number of Patents with low generality	316,602	0.0021	0.053
Number of Patents with high generality	316,602	0.0007	0.036
Number of Patents with Private Assignee	316,604	0.0002	0.02
Number of Patents (Faculty)	51,923	0.008	0.118
Number of Patents (Graduate Students)	136,772	0.0028	0.065
Number of Patents (Undergraduate Students)	25,645	0.0007	0.027
Number of Patents (Staff)	102,262	0.0006	0.028

	Number of Observations	Mean	Standard Deviation
Panel C. Publications			
Any Publications	316,602	0.097	0.296
Number of Publications	316,602	0.302	1.45
Number of High-citation Publications	316,602	0.150	0.841
Number of Low-citation Publications	316,602	0.152	0.752
Number of High-impact Publications	316,602	0.125	0.742
Number of Low-impact Publications	316,602	0.177	0.936
Number of Basic Publications	316,602	0.085	0.568
Number of Applied Publications	316,602	0.165	1.07
Number of Publications cited by patents	316,603	0.043	2.84
Number of Publications (Faculty)	51,923	1.21	1.09
Number of Publications (Graduate Students)	136,772	0.18	0.219
Number of Publications (Undergraduate Students)	25,645	0.02	0.567
Number of Publications (Staff)	102,262	0.08	0.028
Panel D. Career Outcomes			
High-tech Entrepreneurship	197,000	0.0023	0.0483
Entrepreneurship	197,000	0.016	0.1299
Work for Young Firm	197,000	0.0519	
Work for Young High-tech Firm	197,000	0.0091	0.0963
Work for University	197,000	0.4996	
Real Wage	197,000	69,540	93,180
High-tech Entrepreneurship (Faculty)	35,000	0.0016	
High-tech Entrepreneurship (Graduate Students)	91,000	0.0025	
High-tech Entrepreneurship (Undergraduate Students)	19,000	0.0019	
High-tech Entrepreneurship (Staff)	53,000	0.0023	

Table 2: The Effects of Federal Funding Cuts on High-tech Entrepreneurship, Patents, and Publications

This table reports changes in high-tech entrepreneurship, patent, and publication outcomes by university researchers following large and temporary drops in the aggregate availability of CFDA-level federal funding in CFDA codes from which the researchers received funding in the past. The baseline sample is a person-year panel from 2001 through 2017 from 22 universities in UMETRICS data. The dependent variables are: the log of federal funding used by a given researcher (column 1) in a given year; high-tech entrepreneurship is the number of age zero high-tech firms a person works at in a given year (column 2); innovation outcomes indicate whether the person is an inventor of a patent (column 3) or counts the number of her invented patents (column 4) in a given year; column 5 (column 6) indicates if a person receives any publications (uses the number of publications received by a person) in a given year. The key independent variable, Post, equals one following large and temporary drops in the aggregate availability of CFDA-level federal funding in CFDA codes from which the researchers received funding in the past, and zero otherwise, described in Section 2. We include principal investigator (PI) and university-department-year fixed effects in all columns; and person fixed effects in columns 1, 5 and 6. Standard errors are clustered at the person level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Log Federal Funding$_{i,t}$	High-tech Entrepreneurship$_{i,t}$	Any Patents$_{i,t}$	Number of Patents$_{i,t}$	Any Publications$_{i,t}$	Number of Publications$_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
Post$_{i,t}$	-0.3275***	-0.0018**	0.0026**	0.0039***	-0.0120**	-0.0466***
	(0.0586)	(0.00077)	(0.0010)	(0.0013)	(0.0055)	(0.0172)
University$\times$Year$\times$Department FE	Yes	Yes	Yes	Yes	Yes	Yes
PI FE	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	Yes	No	No	No	Yes	Yes
Number of Observations	316,602	197,000	316,602	316,602	316,602	316,602
Adjusted R-squared	0.726	0.011	0.053	0.044	0.554	0.647
Mean of Dependent Variable	9.2	0.0023	0.0023	0.0028	0.097	0.302

Table 3: The Effects of Federal Funding Cuts on High-tech Entrepreneurship, Patents, and Publications by Occupation

This table reports heterogeneous changes in high-tech entrepreneurship, patent, and publication outcomes by university researchers following large and temporary drops in the aggregate availability of CFDA-level federal funding in CFDA codes from which the researchers received funding in the past. These heterogenous changes in researcher's outcomes are shown by occupation: faculty (column 1), graduate students & postdocs (column 2), undergraduate students (column 3), and staff (column 4). The baseline sample is a person-year panel from 2001 through 2017 from 22 universities in UMETRICS data. The dependent variables are: high-tech entrepreneurship in Panel A, which measures the number of age zero high-tech firms the person worked at in a given year; the number of invented patents by a person in given year in Panel B; and the number of publications received by a person in given year in Panel C. The key independent variable, Post, equals one following large and temporary drops in the aggregate availability of CFDA-level federal funding in CFDA codes from which the researchers received funding in the past, and zero otherwise, described in Section 2. We include principal investigator (PI) and university-department-year fixed effects in all specifications; and add person fixed effects in Panel C. Standard errors are clustered at the person level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Occupational Group:	Faculty	Graduate Students and Postdocs	Undergraduate Students	Staff
	(1)	(2)	(3)	(4)
Panel A. Dependent Variable:	High-tech Entrepreneurship$_{i,t}$			
Post$_{i,t}$	-0.000078	-0.0023*	-0.0085	-0.00052
	(0.00103)	(0.0013)	(0.0066)	(0.0017)
University×Year×Department FE	Yes	Yes	Yes	Yes
PI FE	Yes	Yes	Yes	Yes
Number of Observations	35,500	91,000	19,000	53,000
Adjusted R-squared	0.029	0.007	0.26	0.026
Mean of Dependent Variable	0.0016	0.0025	0.0019	0.0023
Panel B. Dependent Variable:	Number of Patents$_{i,t}$			
Post$_{i,t}$	0.0072	0.0038**	-0.0037	0.0006
	(0.0052)	(0.0017)	(0.0047)	(0.0008)
University×Year×Department FE	Yes	Yes	Yes	Yes
PI FE	Yes	Yes	Yes	Yes
Number of Observations	52,172	134,949	25,785	103,696
Adjusted R-squared	0.174	0.067	0.040	0.122
Mean of Dependent Variable	0.008	0.0028	0.0007	0.0006
Panel C. Dependent Variable:	Number of Publications$_{i,t}$			
Post$_{i,t}$	-0.2201***	0.0118	0.0095	-0.0131
	(0.0607)	(0.0281)	(0.0257)	(0.0111)
University×Year×Department FE	Yes	Yes	Yes	Yes
Person FE	Yes	Yes	Yes	Yes
Number of Observations	52,172	134,949	25,785	103,696
Adjusted R-squared	0.651	0.520	0.244	0.537
Mean of Dependent Variable	1.21	0.18	0.02	0.08

Table 4: Heterogeneous Effects of Federal Funding Cuts on Patents by Their Type

This table reports changes in patent outcomes across variety of dimensions by university researchers following large and temporary drops in the aggregate availability of CFDA-level federal funding in CFDA codes from which the researchers received funding in the past. The baseline sample is a person-year panel from 2001 through 2017 from 22 universities in UMETRICS data. The dependent variable is the number of patents by a person in given year: column 1 focuses on patents with low generality and column 2 on high-generality patents (high vs. low generality patents are split by the median generality in each year); column 3 focuses on patents with low forward citations and column 4 on high-citations patents (high-citations patents are patents with normalized number of citations above the median in a given year among patents with at least one citation); column 5 focuses on patents where at least one assignee is a firm. The key independent variable, Post, equals one following large and temporary drops in the aggregate availability of CFDA-level federal funding in CFDA codes from which the researchers received funding in the past, and zero otherwise, described in Section 2. All regressions include principal investigator (PI) and university-department-year fixed effects. Standard errors are clustered at the person level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Number of Patents$_{i,t}$				
	Low Generality	High Generality	Low Citations	High Citations	Private Assignee
	(1)	(2)	(3)	(4)	(5)
Post$_{i,t}$	0.0027***	0.0013**	0.0026***	0.0014**	0.0005**
	(0.0010)	(0.0006)	(0.0010)	(0.0006)	(0.0002)
University$\times$Year$\times$Department FE	Yes	Yes	Yes	Yes	Yes
PI FE	Yes	Yes	Yes	Yes	Yes
Number of Observations	316,602	316,602	316,602	316,602	316,602
Adjusted R-squared	0.047	0.024	0.041	0.033	0.068
Mean of Dependent Variable	0.0021	0.0007	0.0019	0.0009	0.0002

Table 5: Heterogeneous Effects of Federal Funding Cuts on Publications by Their Type

This table reports changes in publication outcomes across variety of dimensions by university researchers following large and temporary drops in the aggregate availability of CFDA-level federal funding in CFDA codes from which the researchers received funding in the past. The baseline sample is a person-year panel from 2001 through 2017 from 22 universities in UMETRICS data. The dependent variable is the number of publications by a person in given year: column 1 focuses on publications in low-impact journals and column 2 on high-impact journals (the split in high- vs. low-impact journals is by the median of the journal impact factor); column 3 focuses on publications with low forward citations and column 4 on high-citations publications (the split in high vs. low publications is by the median number of forward citations in a given year); column 5 focuses on applied publications and column 6 on basic publications (the split in basic vs. applied publications is by the median score of appliedness from Ke (2019); column 7 focuses on publications that cite at least one patent. The key independent variable, Post, equals one following large and temporary drops in the aggregate availability of CFDA-level federal funding in CFDA codes from which the researchers received funding in the past, and zero otherwise, described in Section 2. All regressions include person fixed effects and university-department-year fixed effects. Standard errors are clustered at the person level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Number of Publications$_{i,t}$						
	Low Impact Journal	High Impact Journal	Low Citations	High Citations	Applied	Basic	Cited by Patents
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post$_{i,t}$	-0.0188	-0.0277***	-0.0176*	-0.0290***	-0.0054	-0.0218***	0.0124***
	(0.0119)	(0.0090)	(0.0095)	(0.0105)	(0.0134)	(0.0075)	(0.0041)
University$\times$Year$\times$Department FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	316,602	316,602	316,602	316,602	316,602	316,602	316,602
Adjusted R-squared	0.574	0.598	0.538	0.576	0.610	0.549	0.486
Mean of Dependent Variable	0.125	0.177	0.152	0.150	0.165	0.085	0.043

Table 6: The Effects of Federal Funding Cuts on High-tech Entrepreneurship, Patents, and Publications by Ex-ante Research Grant Timing

This table reports changes in high-tech entrepreneurship, patent, and publication outcomes by university researchers following large and temporary drops in the aggregate availability of CFDA-level federal funding in CFDA codes from which the researchers received funding in the past. The table shows the effects for researchers who received their federal funding more versus less recently. The baseline sample is a person-year panel from 2001 through 2017 from 22 universities in UMETRICS data. The dependent variables are: the log of federal funding used by a given researcher (column 1) in a given year; high-tech entrepreneurship is the number of age zero high-tech firms a person works at in a given year (column 2); innovation outcomes indicate whether the person is an inventor of a patent (column 3) or counts the number of her invented patents (column 4) in a given year; column 5 (column 6) indicates if a person receives any publications (uses the number of publications received by a person) in a given year. The key independent variable, Post, equals one following large and temporary drops in the aggregate availability of CFDA-level federal funding in CFDA codes from which the researchers received funding in the past, and zero otherwise. (Award $<$ 2 years) indicates whether a researcher's federal grant is received within 2 years before the CFDA-level funding shock, and (Award $\geq$ 2 years) indicates if the federal grant is received 2 or more years before the CFDA-level funding shock. We include principal investigator (PI) and university-department-year fixed effects in all columns; and person fixed effects in columns 1, 5 and 6. The last row reports the p-values of the t-test for the difference between the coefficients of Post * (Award $<$ 2 years) and Post * (Award $\geq$ 2 years). Standard errors are clustered at the person level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Log Federal Funding$_{i,t}$	High-tech Entrepreneurship$_{i,t}$	Any Patents$_{i,t}$	Number of Patents$_{i,t}$	Any Publications$_{i,t}$	Number of Publications$_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
Post$_{i,t}$ * (Award $<$ 2 years)	-0.2290***	-0.0012	0.0007	0.0012	-0.0054	-0.0382*
	(0.0808)	(0.00082)	(0.0010)	(0.0010)	(0.0082)	(0.0204)
Post$_{i,t}$ * (Award $\geq$ 2 years)	-0.4940***	-0.0019***	0.0029**	0.0048***	-0.0160**	-0.0580**
	(0.0642)	(0.00071)	(0.0012)	(0.0015)	(0.0063)	(0.0228)
University$\times$Year$\times$Department FE	Yes	Yes	Yes	Yes	Yes	Yes
PI FE	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	Yes	No	No	No	Yes	Yes
Number of Observations	316,602	197,000	316,602	316,602	316,602	316,602
Adjusted R-squared	0.727	0.011	0.053	0.044	0.554	0.647
Mean of Dependent Variable	9.2	0.00225	0.0023	0.0028	0.097	0.302
p-value for the Difference	0.020	0.073	0.091	0.024	0.365	0.477

Table 7: Effect of Federal Funding Shocks on Individual's Overall Funding, Private Funding, and Shares of Federal and Private Funding

The table reports changes in total funding, private funding, and the shares of federal and private funding relied upon by university researchers following large and temporary drops in the aggregate availability of CFDA-level federal funding in CFDA codes from which the researchers received funding in the past. CFDAs are federal programs from which the researchers receive funding. If a researcher received funding from multiple CFDA codes, we take the CFDA code from which she received the most money. The main independent variable, Post, equals one following large and temporary drops in the aggregate availability of CFDA-level federal funding in CFDA codes from which the researchers received funding in the past, and zero otherwise, described in Section 2. The baseline sample is a person-year panel from 2001 through 2017 from 22 universities in UMETRICS data. The dependent variables are the log of all funding (column 1), the log of private funding (columns 2–3), and the share of total funding amount, for a researcher in a given year, from the federal government (column 4) and private companies (columns 5). In column 3, we focus on researchers in fields that tend to get at least some private funding by restricting the sample to university-by-field combinations with an above-median average share private funding. All regressions include university-by-year-by-department and principal investigator (PI) fixed effects. Standard errors are clustered at the person level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

Dependent Variable:	Log All Funding$_{i,t}$	Log Private Funding$_{i,t}$		Share Federal$_{i,t}$	Share Private$_{i,t}$
	(1)	(2)	(3)	(4)	(5)
Post$_{i,t}$	-0.1556**	0.1401	0.2536*	-0.0411***	0.0302***
	(0.0725)	(0.1515)	(0.1566)	(0.0115)	(0.0089)
University$\times$Year$\times$Department FE	Yes	Yes	Yes	Yes	Yes
PI FE	Yes	Yes	Yes	Yes	Yes
Number of Observations	316,602	316,602	157,763	316,602	316,602
Adjusted R-squared	0.404	0.435	0.455	0.316	0.285

Table 8: Summary Statistics by Funding Source

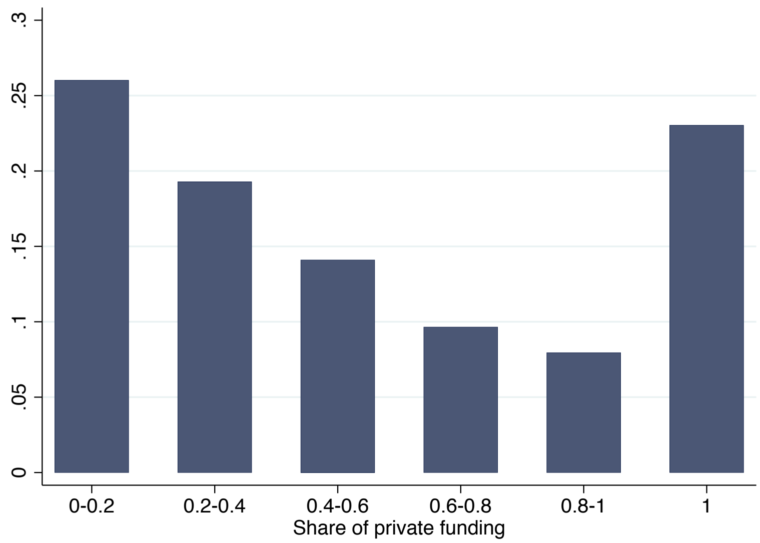
Table shows summary statistics for funding characteristics, research team sizes, and research outcomes for people funded by the U.S. Federal Government (column “Federal”) and by the private sector (e.g., corporations or non-profits; column “Private”). The last column presents the p-values of t-tests for the difference in means between federal and private awards. Both samples are person-year panels from 2001 through 2017 from 22 universities in UMETRICS data. All patent (publications) outcomes measure the number and characteristics of patents (publications) of which the majority of inventors (or authors) are funded by federal or private awards.

Funding Type:	Federal	Private	T-test p-value
UMETRICS Outcomes:			
Number of Awards	168,123	56,888	
Number of Employees	482,990	137,562	
Mean Total Expenditure (thousands)	367.2	216.4	0.000
Median Total Expenditure (thousands)	123.4	50.0	
Mean Grant Duration (years)	3.03	2.96	0.000
Median Grant Duration (years)	3	3	
Mean Team Size	7.42	4.75	0.000
Median Team Size	4	2	
Patent Outcomes:			
Number of Patents	6,083	1,303	
Mean Patent Originality	0.274	0.291	0.031
Mean Patent Generality	0.185	0.143	0.000
Mean Adjusted Citation (by filing year and field)	1.19	0.895	0.016
Percent of Assignees That Are Private Firms	3.3	5.7	0.000
Publications Outcomes:			
Number of Publications	448,714	61,293	
Mean Journal Impact Factor	2.63	2.48	0.000
Mean Citation (with 3 year of publishing)	21.2	20.8	0.183
Mean Citation (all years)	42.4	39.8	0.000
Mean Appliedness Score	0.102	0.184	0.000
Mean Citations by Patents	0.125	0.127	0.802

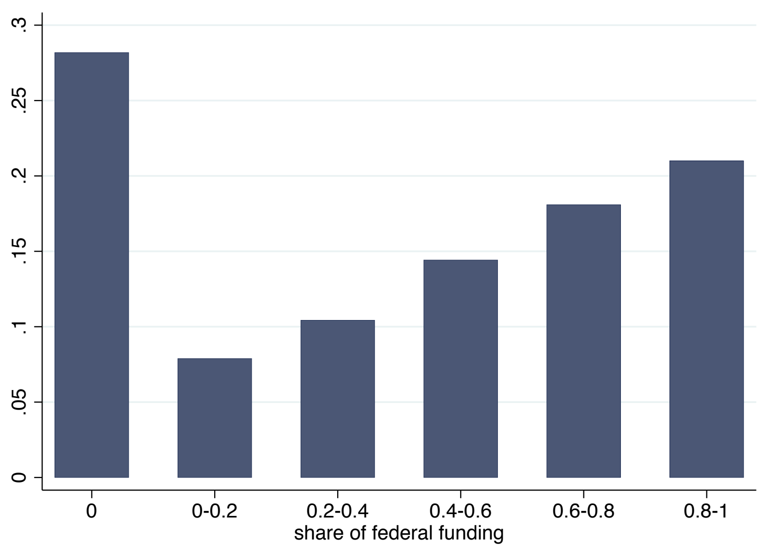
A Appendix: Additional Tables and Figures

Figure A.1: Distribution of the Private and Federal Share of Funding Among People With Some Private Funding

Panel A. Share of Private Funding

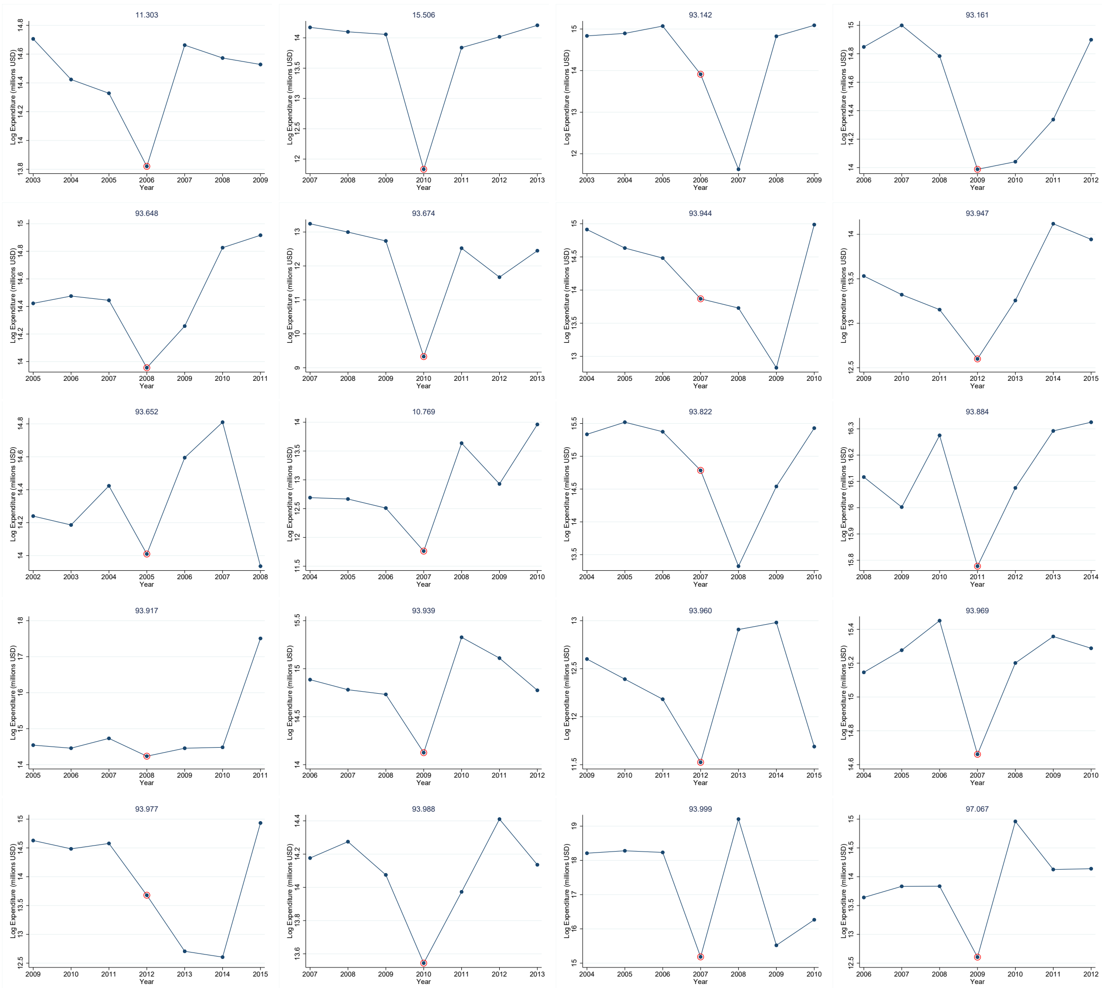


Panel B. Share of Federal Funding



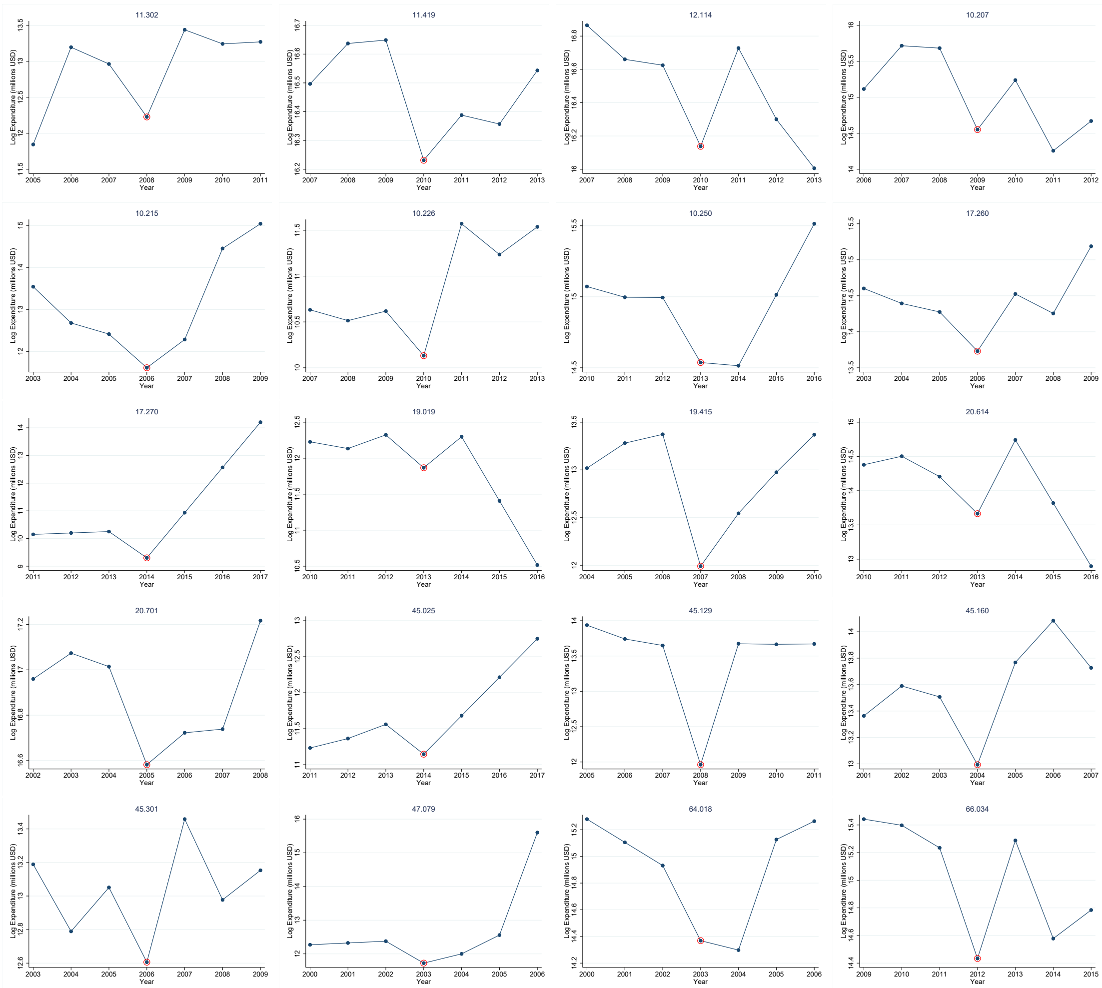
This figure shows the distribution of the private and federal share of funding among people with some private funding, which are 23% of researcher-years. Panel A shows the share of private funding, and Panel B shows the share of federal funding.

Figure A.2: All CFDA Shocks (Part I of III)



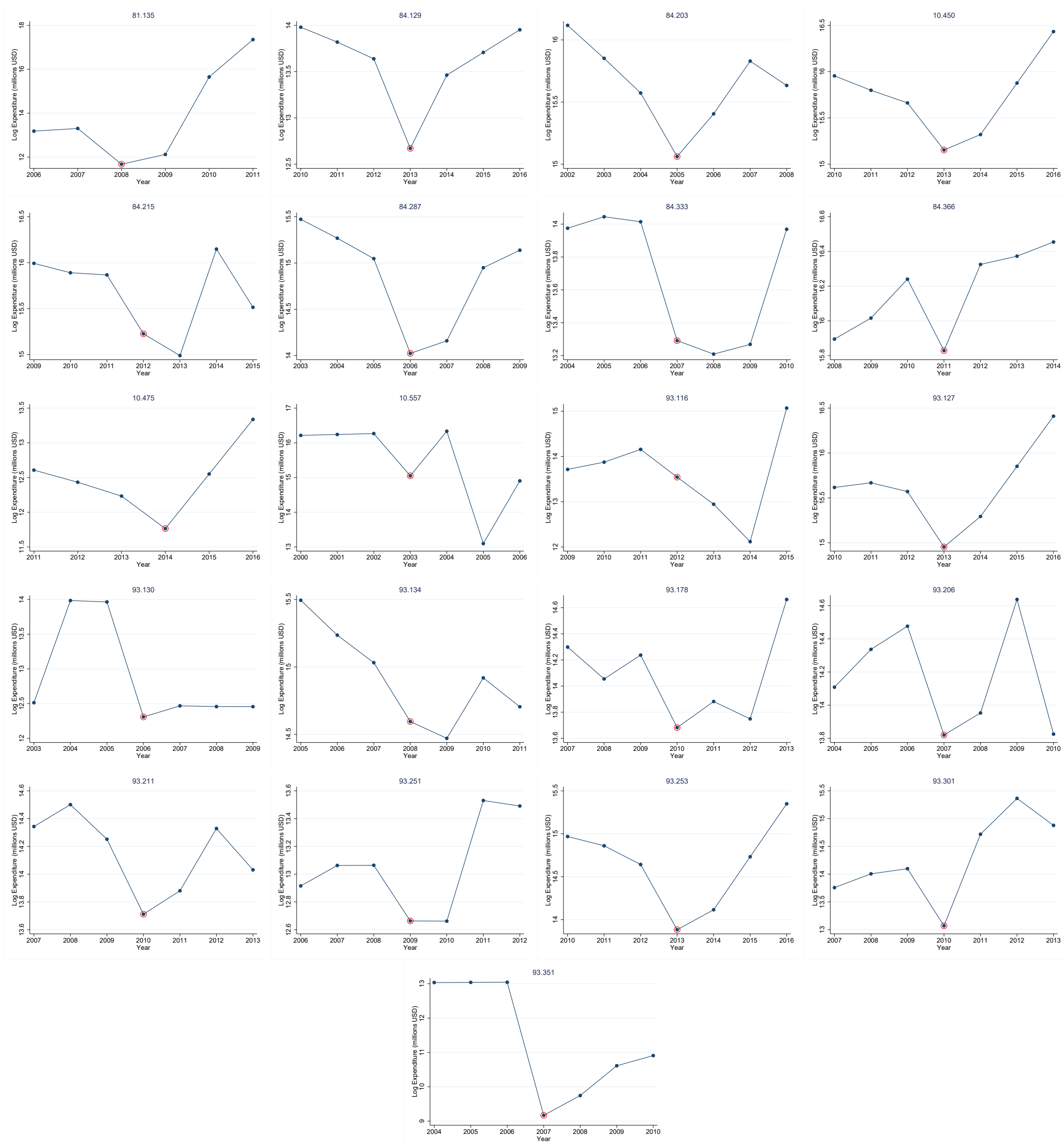
This figure shows government-wide CFDA-level R&D expenditure around all the shocks we use in analysis. The year in which the large negative shock occurred is denoted with a red circle. These shocks provide the source of variation for the event-study analysis. CFDAs are fields in which researchers receive funding.

Figure A.3: All CFDA Shocks (Part II of III)



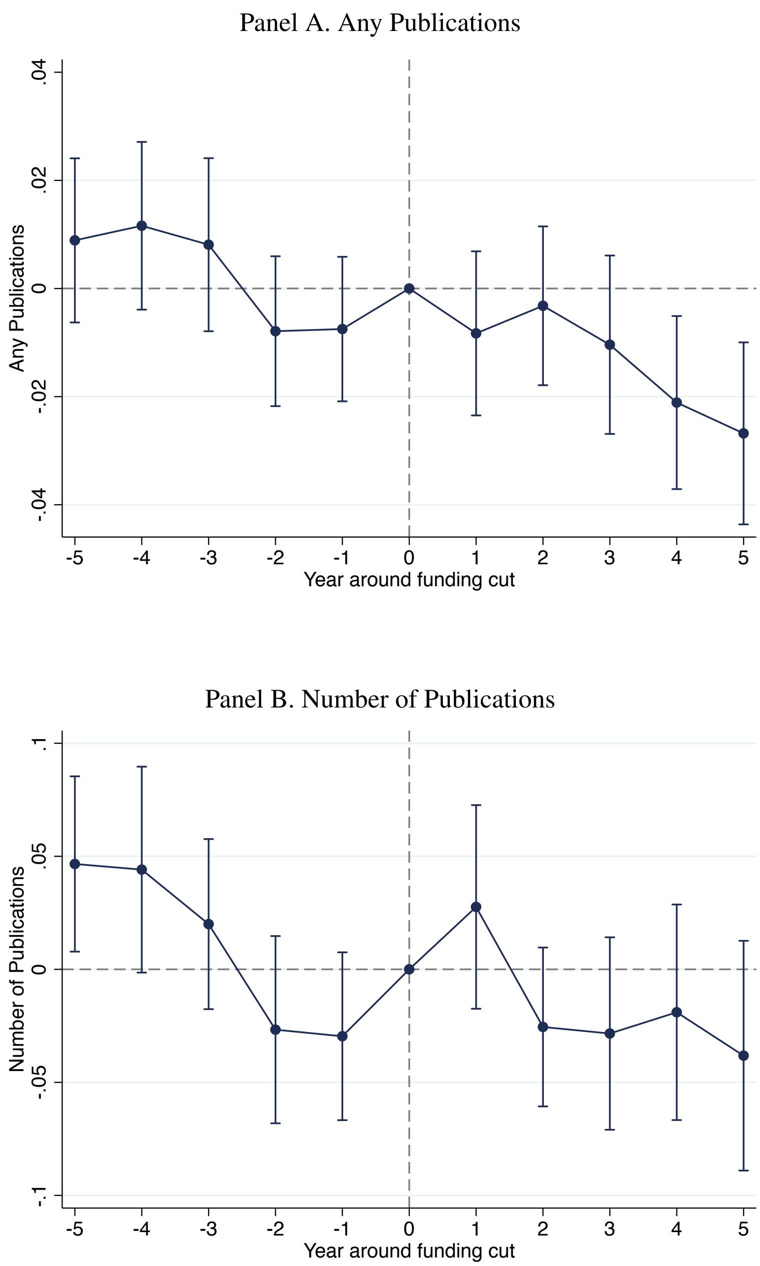
This figure shows government-wide CFDA-level R&D expenditure around all the shocks we use in analysis. The year in which the large negative shock occurred is denoted with a red circle. These shocks provide the source of variation for the event-study analysis. CFDAs are fields in which researchers receive funding.

Figure A.4: All CFDA Shocks (Part III of III)



This figure shows government-wide CFDA-level R&D expenditure around all the shocks we use in analysis. The year in which the large negative shock occurred is denoted with a red circle. These shocks provide the source of variation for the event-study analysis. CFDAs are fields in which researchers receive funding.

Figure A.5: Effect of Large, Negative Federal Funding Shocks on Number of Publications



This figure shows estimates of Equation 2, describing the effect of large, negative federal funding shocks to a researcher's primary field of study on individual outcomes. In this case, the dependent variable is an indicator for having any publications (Panel A) and the number of publications (Panel B). The regression includes person fixed effects and university-department-year fixed effects. The figure includes 95% confidence intervals.

Table A.1: Balance Test. Compare Researchers in Treated and Control Groups Before Federal Funding Cuts

This table compares researchers in the control and the treated groups (before the treatment take place) and shows that the ex-ante characteristics of the treated researchers do not differ significantly from the characteristics of the control researchers. The key independent variable, Treated, equals one for researchers who experience large and temporary drops in the aggregate availability of CFDA-level federal funding in CFDA codes from which the researchers received funding in the past. CFDAs are federal programs from which the researchers receive funding. If a researcher received funding from multiple CFDA codes, we take the CFDA code from which she received the most money. The baseline sample is a person-year panel from 2001 through 2017 from 22 universities in UMETRICS data. The dependent variables are measured from the U.S. patent and publications data matched with the UMETRICS data. The dependent variable are: the Share of Federal Funding is the share of the researchers' funding coming from Federal US Government sources (column 1); the Share of Private Funding is the share of the funding coming from private sources (e.g., corporations or non-profits) in column 2; log Total Funding is the total amount of research funding expenditure by a researcher in a given year aggregating over all grants the researcher receives (column 3). In columns 4–6, the dependent variables measure a probability of a different researcher's occupations: faculty (column 4), graduate students and postdocs (column 5), and undergraduate students (column 6). The innovation outcomes indicate whether the person is an inventor of a patent (column 7) or counts the number of her invented patents (column 8) in a given year; column 9 (column 10) indicates if a person receives any publications (uses the number of publications received by a person) in a given year. We include university-department-year fixed effects in all columns. Standard errors are clustered at the person level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Share of Federal Funding	Share of Private Funding	Log Total Funding	Faculty	Graduate Students and Postdocs	Undergraduate Students	Any Patents	Number of Patents	Any Publications	Number of Publications
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treated	0.0052	-0.0059	-0.0496	0.0088	-0.0081	-0.0054	-0.0007	-0.0012	-0.0026	-0.0282
	(0.0061)	(0.0071)	(0.0515)	(0.0055)	(0.0063)	(0.0036)	(0.0007)	(0.0009)	(0.0037)	(0.0184)
University $\times$ Year $\times$ Department FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	291,092	291,092	291,092	291,092	291,092	291,092	291,092	291,092	291,092	291,092
Adjusted R-squared	0.094	0.076	0.178	0.066	0.129	0.137	0.008	0.005	0.123	0.065

Table A.2: The Effects of Federal Funding Cuts on Additional Career Outcomes

This table reports changes in additional researcher's career outcomes of university researchers following large and temporary drops in the aggregate availability of CFDA-level federal funding in CFDA codes from which the researchers received funding in the past. The baseline sample is a person-year panel from 2001 through 2017 from 22 universities in UMETRICS data. The dependent variables are measured from the restricted-use US Census/IRS W-2 data matched with the UMETRICS data. In column 1, Entrepreneurship is the number of age zero firms (not necessarily high-tech) a person works at in a given year, and in column 2, Work for Young Firm is an indicator for a person working at any firm five years of age or younger in a given year. In column 3, Work for Young High-tech Firm is the number of high-tech firms that are between 1 and 5 years old that a person works at in a given year. In column 4, Work for Any University is an indicator for person working at a university, identified from the EINs in US Census/IRS W-2 data using universities' EINs. In column 5, Work for Research University is an indicator for person working at a research university, defined using the Carnegie Classifications: R1 institutions are doctoral granting universities with "very high research activity." In column 6, Log(Wage) is the log of real wage in 2014 dollars, where wage is the maximum wage revived from any single source in a given year. The key independent variable, Post, equals one following large and temporary drops in the aggregate availability of CFDA-level federal funding in CFDA codes from which the researchers received funding in the past, and zero otherwise. We include principal investigator (PI) and university-department-year fixed effects in all columns. Standard errors are clustered at the person level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Entrepreneurship$_{i,t}$	Work for Young Firm$_{i,t}$	Work for Young High-tech Firm$_{i,t}$	Work for Any University$_{i,t}$	Work for Research University$_{i,t}$	Log(Wage$_{i,t}$)
	(1)	(2)	(3)	(4)	(5)	(6)
Post$_{i,t}$	0.0055**	0.0256***	-0.0051**	-0.164***	-0.125***	-0.013
	(0.0027)	(0.0064)	(0.00205)	(0.0169)	(0.0141)	(0.148)
University×Year×Department FE	Yes	Yes	Yes	Yes	Yes	Yes
PI FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	197,000	316,602	316,602	316,602	316,602	316,602
Adjusted R-squared	0.003	0.033	0.058	0.289	0.329	0.322
Mean of Dependent Variable	0.016	0.052	0.0091	0.50	0.41	$69,540

Table A.3: The Effects of Federal Funding Jumps on High-tech Entrepreneurship, Patents, and Publications

This table reports changes in high-tech entrepreneurship, patent, and publication outcomes by university researchers following large and temporary increases in the aggregate availability of CFDA-level federal funding in CFDA codes from which the researchers received funding in the past. The baseline sample is a person-year panel from 2001 through 2017 from 22 universities in UMETRICS data. The dependent variables are: the log of federal funding used by a given researcher (column 1) in a given year; high-tech entrepreneurship is the number of age zero high-tech firms a person works at in a given year (column 2); innovation outcomes indicate whether the person is an inventor of a patent (column 3) or counts the number of her invented patents (column 4) in a given year; column 5 (column 6) indicates if a person receives any publications (uses the number of publications received by a person) in a given year. The key independent variable, Post, equals one following large and temporary increases in the aggregate availability of CFDA-level federal funding in CFDA codes from which the researchers received funding in the past, and zero otherwise. We include principal investigator (PI) and university-department-year fixed effects in all columns; and person fixed effects in columns 1, 5 and 6. Standard errors are clustered at the person level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Log Federal Funding$_{i,t}$	High-tech Entrepreneurship$_{i,t}$	Any Patents$_{i,t}$	Number of Patents$_{i,t}$	Any Publications$_{i,t}$	Number of Publications$_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
Post$_{i,t}$	0.2504*	0.00029	-0.0027	-0.0028	0.0136*	0.0376*
	(0.1498)	(0.00077)	(0.0020)	(0.0023)	(0.0076)	(0.0223)
University×Year×Department FE	Yes	Yes	Yes	Yes	Yes	Yes
PI FE	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	Yes	No	No	No	Yes	Yes
Number of Observations	230,175	150,000	230,175	230,175	230,175	230,175
Adjusted R-squared	0.753	0.015	0.054	0.045	0.553	0.637
Mean of Dependent Variable	9.3	0.00235	0.0028	0.0035	0.104	0.322

Table A.4: The Effects of Federal Funding Cuts on High-tech Entrepreneurship, Patents, and Publications at the Research Lab Level

This table reports changes in research lab size, funding, high-tech entrepreneurship, patent, and publication outcomes by university researchers following large and temporary drops in the aggregate availability of CFDA-level federal funding in CFDA codes from which the researchers received funding in the past. The baseline sample is a research-lab-year panel from 2001 through 2017 from 22 universities in UMETRICS data. The dependent variables are aggregated at each research lab in a given year: the number of researchers in the lab (column 1); the log of federal funding received by the lab (column 2); the log of all funding received by the lab (column 3); high-tech entrepreneurship is the number of age zero high-tech firms researchers (from the lab) works at in a given year (column 4); innovation outcomes indicate whether there is researcher who is an inventor of a patent (column 5) or an author of a publication (column 7) or counts the number of patents (column 6) or publications (column 8). The key independent variable, Post, equals one following large and temporary drops in the aggregate availability of CFDA-level federal funding in CFDA codes from which the researchers received funding in the past, and zero otherwise. We include research lab and university-department-year fixed effects in all columns. Standard errors are clustered at the lab level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Lab Size$_{i,t}$ (1)	Log Federal Funding$_{i,t}$ (2)	Log All Funding$_{i,t}$ (3)	High-tech Entrepreneurship$_{i,t}$ (4)	Any Patents$_{i,t}$ (5)	Number of Patents$_{i,t}$ (6)	Any Publications$_{i,t}$ (7)	Number of Publications$_{i,t}$ (8)
Post$_{i,t}$	-0.3706**	-0.2556**	-0.1193	-0.0011	0.0085*	0.0159*	-0.0119	-0.0721*
	(0.1747)	(0.1213)	(0.0960)	(0.0015)	(0.0048)	(0.0093)	(0.0184)	(0.0371)
University×Year×Department FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lab FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Labs	7,054	7,054	7,054	5,400	7,054	7,054	7,054	7,054
Adjusted R-squared	0.566	0.644	0.635	0.012	0.039	0.021	0.479	0.489
Mean of Dependent Variable	2.62	10.5	10.8	0.0059	0.013	0.018	0.23	1.12

Table A.5: Robustness. The Effects of Federal Funding Cuts on High-tech Entrepreneurship, Patents, and Publications: Cluster Standard Errors at University-By-Department Level

This table shows that the main results in Table 2 are robust to clustering standard errors at university-by-department level, and reports changes in high-tech entrepreneurship, patent, and publication outcomes by university researchers following large and temporary drops in the aggregate availability of CFDA-level federal funding in CFDA codes from which the researchers received funding in the past. The baseline sample is a person-year panel from 2001 through 2017 from 22 universities in UMETRICS data. The dependent variables are: the log of federal funding used by a given researcher (column 1) in a given year; high-tech entrepreneurship is the number of age zero high-tech firms a person works at in a given year (column 2); innovation outcomes indicate whether the person is an inventor of a patent (column 3) or counts the number of her invented patents (column 4) in a given year; column 5 (column 6) indicates if a person receives any publications (uses the number of publications received by a person) in a given year. The key independent variable, Post, equals one following large and temporary drops in the aggregate availability of CFDA-level federal funding in CFDA codes from which the researchers received funding in the past, and zero otherwise. We include principal investigator (PI) and university-department-year fixed effects in all columns; and person fixed effects in columns 1, 5 and 6. Standard errors are clustered at the person level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Log Federal Funding$_{i,t}$	High-tech Entrepreneurship$_{i,t}$	Any Patents$_{i,t}$	Number of Patents$_{i,t}$	Any Publications$_{i,t}$	Number of Publications$_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
Post$_{i,t}$	-0.3275***	-0.00181***	0.0026***	0.0039***	-0.0120	-0.0466
	(0.1160)	(0.000601)	(0.0009)	(0.0014)	(0.0139)	(0.0413)
University×Year×Department FE	Yes	Yes	Yes	Yes	Yes	Yes
PI FE	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	Yes	No	No	No	Yes	Yes
Number of Observations	316,602	197,000	316,602	316,602	316,602	316,602
Adjusted R-squared	0.726	0.011	0.053	0.044	0.554	0.647
Mean of Dependent Variable	9.2	0.00225	0.0023	0.0028	0.097	0.302

Table A.6: Robustness. The Effects of Federal Funding Cuts on High-tech Entrepreneurship, Patents, and Publications: Cluster Standard Errors at CFDA Level

This table shows that the main results in Table 2 are robust to clustering standard errors at CFDA code level. CFDAs are federal programs from which the researchers receive funding. If a researcher received funding from multiple CFDA codes, we take the CFDA code from which she received the most money. The table reports changes in high-tech entrepreneurship, patent, and publication outcomes by university researchers following large and temporary drops in the aggregate availability of CFDA-level federal funding in CFDA codes from which the researchers received funding in the past. The baseline sample is a person-year panel from 2001 through 2017 from 22 universities in UMETRICS data. The dependent variables are: the log of federal funding used by a given researcher (column 1) in a given year; high-tech entrepreneurship is the number of age zero high-tech firms a person works at in a given year (column 2); innovation outcomes indicate whether the person is an inventor of a patent (column 3) or counts the number of her invented patents (column 4) in a given year; column 5 (column 6) indicates if a person receives any publications (uses the number of publications received by a person) in a given year. The key independent variable, Post, equals one following large and temporary drops in the aggregate availability of CFDA-level federal funding in CFDA codes from which the researchers received funding in the past, and zero otherwise. We include principal investigator (PI) and university-department-year fixed effects in all columns; and person fixed effects in columns 1, 5 and 6. Standard errors are clustered at the person level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Log Federal Funding$_{i,t}$	High-tech Entrepreneurship$_{i,t}$	Any Patents$_{i,t}$	Number of Patents$_{i,t}$	Any Publications$_{i,t}$	Number of Publications$_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
Post$_{i,t}$	-0.3275***	-0.00181**	0.0026***	0.0039***	-0.0120	-0.0466
	(0.1160)	(0.000846)	(0.0009)	(0.0014)	(0.0139)	(0.0413)
University×Year×Department FE	Yes	Yes	Yes	Yes	Yes	Yes
PI FE	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	Yes	No	No	No	Yes	Yes
Number of Observations	316,602	197,000	316,602	316,602	316,602	316,602
Adjusted R-squared	0.726	0.011	0.053	0.044	0.554	0.647
Mean of Dependent Variable	9.2	0.00225	0.0023	0.0028	0.097	0.302

B Appendix: Description of Data Sources and Sample Construction

This section discusses the data sources and how they are combined to create our estimation sample. Our analysis is based on human resource records from universities (Section B.1). We first merge the data with expenditures in federal assistance programs from Single Audit (Section B.2). We then link the university researchers to inventors to get patenting outcomes (Section B.3) and publications (Section B.4). Finally, we obtain career outcomes from confidential administrative data at the U.S. Census Bureau (Section B.5).

B.1 UMETRICS Data

We use new grant administration accounting records from the IRIS UMETRICS program to measure funding of university researchers. Universities contribute grant-level accounting data to this program, which is administered by the Institute for Research on Innovation and Science (IRIS) at the University of Michigan. Our sample covers 22 universities, accounting for more than 15% of federal R&D expenditures, but the project is expected to become a national program.

For each grant, we observe both the name of the external funding source as well as the CFDA code for federal agency sponsors. We use the CFDA codes and names of external funders to determine if a grant came from a federal government agency, private firm, or other sources.[48] We observe all of the research grants received by each researcher in each year as well as the expenditures for each grant. We calculate the fraction of a researcher's expenditures that comes from each CDFA code (from the federal government), as well as the fraction that is accounted for by private firms and other sources. We also observe each researcher's occupation classification (e.g., faculty, graduate student or post-doc, undergraduate student, and other) and department (e.g., physics, biology, etc). Occupations defining our "graduate students/post-docs" category include: Graduate Student, Post Graduate Research, and Research (Staff Scientist, Research Analyst, Technician). Occupations defining our "staff" category include: Clinical, Research Facilitation (Research Support, Research Administration, Research Coordinator), Technical Support, Instructional, and Other Staff.

[48]While the coverage of federal grants is complete, the coverage of non-federal grants is incomplete at some universities. Since we are interested in the full picture of university researchers' funding and private funding plays an important role in our mechanism, we exclude from our sample universities that do not supply information on funding from non-federal sources.

B.2 Spending Shocks

We measure federal funding shocks at CFDA-program level using Single Audits. All non-federal entities that spend \$500,000 or more of federal awards in a year (\$300,000 for fiscal years ending on or before December 30, 2003) are required to obtain an annual audit in accordance with the Single Audit Act Amendments of 1996. A Single Audit includes an examination of a recipient's financial records, financial statements, federal award transactions and expenditures, the general management of its operations, internal control systems, and federal assistance it received during the year.

We collect our data from the Federal Audit Clearinghouse, to which the Single Audits are submitted. The data contains both R&D and non-R&D expenditures by CFDA program and year. We focus on R&D expenditures at the CFDA-level and define negative shocks to a CFDA code as being large if they meet the following conditions: (1) the total expenditure of federal funding at the CFDA code level drops by at least 40% from the previous year; (2) the decline in funding is temporary and the funding level reverts back to the pre-shock level at some later point in time; (3) there is no big positive or negative funding changes (>20% or <-20%) in the two years preceding the shock. In our data there are 61 CFDA codes with one negative shock that fits these three criteria, which are shown dynamically in Figures A.2-A.4 (discussed above). We consider CFDA codes that never had a large negative shock (i.e., no drops of more than 40% from one year to the next) as the control group, and we have 210 CFDA codes in this group. Thus, the event of interest for a given employee is a large negative shock to funding in their CFDA code. An employee is treated if she gets more than half of her funding from one of the treated CFDA codes (before the shock), and is control if she gets more than half of her funding from the control CFDA codes. We create time to event dummy variables indicating the years before and after the event (i.e., large negative shock to funding in CFDA code), as well as a post indicator which take on the value 1 in the years after the large negative shock and 0 otherwise.

Case Histories

A detailed examination of the history of our shocks suggests that in general, there is a decision to increase one program's funding in a particular year, leading other neighboring programs to receive arbitrary cuts. There is no public record explaining *why* one program was temporarily on the chopping block, and our interviews with government officials confirm that they are unwilling to speak on the record about these cuts, regardless of whether the decision was legislated by Congress or determined by the agency.

However, in an interview, the Deputy Director for Extramural Research at the National Institutes of Health explained to us in general how one-time shocks may occur. He said, “Congress may tell us to spend more money on Alzheimer’s disease, and that means we’ll spend less money on, say, hip fractures. Or they might tell us to spend more money on Down’s syndrome, perhaps we’ll spend less money on cerebral palsy. This does not mean someone made a deliberate decision to spend less on cerebral palsy. The particular area of science is being favored for funding; the opportunity cost is that something else must go down. Some of it is the luck of the draw. It is also driven by variation across broader areas [above the CFDA level] in the strictness of the payline. So some of this may be a random event; there may have been a push to fund some other area of science, either from congress or strategic planning; because that area got funded more, it would be more difficult for a grant in another CFDA within the broader area to get funded unless it got an unbelievable score.”[49] We cannot, unfortunately, establish that one program among several options was chosen for a cut on a purely random basis. However, the fact that the funding levels in our shocks return to baseline in the following year is strong evidence of some degree of arbitrary decision-making, since demand or opportunities in major disease areas–or, for example, water desalination as we highlight below–do not fluctuate dramatically on a year-to-year basis.

That said, it is helpful to describe the budgetary process around some of our shocks, to highlight how they occur. One of our shocks is to “Animal Health and Disease Research” at the U.S. Department of Agriculture. The “Food, Conservation, and Energy Act of 2008”[50] reauthorized funding for this area until 2012, suggesting that policymakers did not see meaningful changes in opportunities in this area in the medium term. However, the 2009 budget cut this item to zero.[51] The budget explains that there are increases in some research programs “totaling more than $43 million. These increases are offset by the reduction of $88 million in lower priority programs.” One of the expanding programs is “an increase of $19 million for the Department’s bioenergy and biobased fuels research initiative,” while the “Animal Health and

[49] We spoke with Dr. Michael Lauer on May 4, 2022.

[50] https://www.congress.gov/bill/110th-congress/house-bill/6124

[51] The 2009 budget is not available online except via the Wayback Machine but can be requested from the authors. https://web.archive.org/web/20150914203604/https://www.fsa.usda.gov/Assets/USDA-FSA-Public/usdafiles/AboutFSA/fy09budsum.pdf

Disease Research" was reduced from $5 million to zero. In this particular case, it is easy to imagine how the focus on clean energy at this time led to cuts that were, for all intents and purposes, arbitrary in other areas. In the following year, the "Animal Health and Disease Research" program was funded at $3 million.[52]

A second example is the "Water Desalination Research and Development" program at the U.S. Department of the Interior (DOI). Here, despite increased funding requests from DOI, Congress enacted a significant decline for 2010, which may have reflected increasing funds for a particular desalination project, the "Long Beach Area Water Reclamation Project."[53] Note again that the fact that funding returns to the previous level in the following year offers some evidence that the cut was arbitrary. While we do not observe any rationale in public documents for the Congressional appropriations, in this case since we do observe the agency requesting *more* funding for this program it does not seem likely that a decline in opportunities for researching desalination motivated the cut.

B.3 Patent Data

Patent data are from the PatentsView database, which contains bibliographic information on all patents granted by the United States Patent and Trademark Office (USPTO).[54] Data on patent inventors from PatentsView were linked linked to UMETRICS employees, allowing us to measure each researcher's patenting activity.[55][56]

In addition to the number of granted patents, we construct several variables to measure characteristics of patents that are standard in the literature. The first is the number of forward citations, which we normalize by patent class and by year to adjust for the systematic

[52] https://web.archive.org/web/20150918175803/https://www.fsa.usda.gov/Assets/USDA-FSA-Public/usdafiles/AboutFSA/fy11budsum.pdf

[53] See https://www.usbr.gov/budget/2010/CONTENTS.pdf and https://www.usbr.gov/budget/2011/Contents.pdf.

[54] Established in 2012, PatentsView longitudinally links inventors, assignees, locations and patenting activity using bulk data from the USPTO on published patent applications (2001-present) and granted patents (1976-present).

[55] The matches were obtained by comparing names, affiliations, and grant numbers and constructing a similarity measure based on the textual similarity of the last names, middle initials, and first names. In addition, our matching algorithm examined the university affiliation of the employee with the assignee name listed on the patent and the geographic location listed for the inventor. After comparing names and affiliations, the decision of whether or not a pair matches was based on empirical probabilities from a training dataset of known matches.

[56] Note an inventor does not need to be paid on a grant by a UMETRICS univeristy in the year of patent application to be included in the data, these applications may be from before or after an inventor is observed in UMETRICS.

differences across classes and years.[57] Forward citations are informative about the impact of a patent on future research. The second measure is generality. A high generality score indicates that the patent influenced subsequent innovations in a variety of fields (Trajtenberg et al. 1997).[58] The third measure is originality. The originality score will be low if a patent cites previous patents in a narrow set of technologies, whereas citing patents in a wide range of fields leads to a high score.[59]The last measure is whether the assignee is a private company. We use the name of the assignees to identify whether a patent is assigned to a private company or other entities (e.g., universities).

B.4 Publications Data

The IRIS UMETRICS data match researchers to PubMed publications based on author names. PubMed is a database developed by the National Center for Biotechnology Information (NCBI) at the National Library of Medicine (NLM). The primary data resource is MEDLINE, the NLM's premier bibliographic database covering the fields of medicine, nursing, dentistry, veterinary medicine, the health care system, and the preclinical sciences, such as molecular biology. MEDLINE contains bibliographic citations and author abstracts from about 4,600 biomedical journals published in the United States and 70 other countries. All content in PubMed ultimately comes from publishers of biomedical journals, and journals that are to be included in MEDLINE are subject to a selection process. The Fact Sheet [https://www.nlm.nih.gov/medline/medline_journal_selection.html] on Journal Selection for Index Medicus/MEDLINE describes the journal selection policy, criteria, and procedures for data submission.

We consider two measures of publication quality: the impact factor of the journal and the number of forward citations (normalized by year), both of which are from the Microsoft Academic Graph dataset.[60] We define a journal as *high (low) impact* if the impact factor is

[57]The citations data, from Babina et al. (2019), are updated as of the end of 2019.

[58]Generality for patent i is defined as $1 - \sum_j s_{ij}^2$, where s_{ij} is the percentage of citations received by patent i that belong to patent class j. Thus, if a patent is cited by subsequent patents that belong to a wide range of fields the measure will be high, whereas if most citations are concentrated in a few fields it will be low (close to zero).

[59]Originality for patent i is defined as $1 - \sum_j c_{ij}^2$, where c_{ij} is the percentage of citations that patent i makes that belong to patent class j.

[60]See here for an overview of the Microsoft Academic Graph data.

above (below) the median in a given year, and we define a publication as *high (low) citation* if the number of citations is above (below) the median in a given year and field.

In addition, we consider two measures of the degree to which a publication is basic or applied. The first measure is a score for appliedness based on terms related to clinical research from Ke (2019). Ke (2019) learns vector representations of controlled vocabularies assigned to Medline articles to obtain a translational axis that points from basic science to clinical medicine. The projected position of a term on the translational axis, expressed by a continuous quantity, indicates the term's "appliedness." The position of an article, determined by the average location over its terms, quantifies the degree of its appliedness, which is referred to as the level score. We define an *applied* (or *basic*) publication as a publication with the level score above (or below) median. The second measure is an indicator variable for whether a publication is subsequently cited by any patents (Marx and Fuegi 2020).

B.5 Entrepreneurship and Employment

We obtain career outcomes from confidential administrative data at the U.S. Census Bureau and the Internal Revenue Service (IRS), including the Business Register (BR), the Longitudinal Business Database (BR/LBD), W-2 tax records, and unemployment insurance wage records as captured through the Longitudinal Employer Household Dynamics (LEHD) program.

We construct career outcomes for each UMETRICS individual by first linking them to employment and wage information contained in W-2 tax records and the LEHD Person History File (PHF).[61] The W-2 records are crucial for our setting because, unlike the LEHD PHF, they include graduate student stipends. By linking UMETRICS individuals to these administrative data sources, we are able, with a high degree of confidence, to track each person's full domestic job history.

Both the W-2 records and the LEHD PHF include identifiers that allow us to link firm-level information to each record. Characteristics of employers include age, industry, annual number

[61] The LEHD PHF is derived from state unemployment insurance (UI) records and contains quarterly information on wages for nearly the universe of individuals in participating states as well as from the federal government (McKinney and Vilhuber, 2011). The W-2 records include annual wages with complete coverage for all states from 2005 to 2017. They are reported to the IRS by individuals' employers and are required for any employee with tax withholdings or for whom taxes would have been withheld if not for an exemption claim. This includes industries and workers who are not covered by unemployment insurance.

of employees, annual payroll, and whether the employer is a university. This information is sourced from the BR/LBD, the LEHD Employer Characteristics File (ECF), and the Integrated Postsecondary Education Data System (IPEDS).[62] Crucial for our analysis, IPEDS provides the EIN for a comprehensive list of universities, allowing us to identify earnings that UMETRICS individuals receive from universities. These datasets are combined to create a complete job history panel.

Using this full panel of linked data, we construct the following key outcome variables: 1) a count of the number of age-zero high-tech firm the individual works at (*high-tech entrepreneurship*)[63]; 2) a count of the number of age zero firms an individual works at (*entrepreneurship*); 3) an indicator for whether the individual works at a firm aged greater than zero but five years or fewer (*work for young firm*); 4) a count of the number of high-tech firm aged greater than zero but five years or fewer where an individual works (*work for young high-tech firm*); 5) an indicator for whether the individual works at a university (*work for university*)[64]; 6) an indicator for whether the individual works for a Research 1 institution according to the Carnegie Classification of Institutions of Higher Education.[65] 7) log wages, in real 2014 dollar defined as an individual's wage using their dominant job—that is the job from which she are paid the most. Together, these outcomes characterize the entrepreneurial and employment activity of each person-year. Panel D of Table 1 provides statistics on these career outcomes for our main regression sample used in Section 3.1.

[62]The BR is the Census Bureau's comprehensive list of all business establishments in the United States and contains information on each establishment's employment, payroll, industry (NAICS code), EIN, and a firm identifier developed by the Census Bureau (DeSalvo et al., 2016). The LBD links establishments in the BR over time, which allows us to obtain the age of each firm (Jarmin and Miranda, 2002). The LEHD ECF is the universe of establishments that report earnings to state unemployment insurance agencies, and contains information on employment, payroll, industry, and the Census-developed firm identifier (McKinney and Vilhuber, 2011). IPEDS is a database maintained by the National Center for Education Statistics (NCES), and provides a wide variety of information on colleges, universities, and technical and vocational schools in the United States.

[63]High-tech NAICS are defined according to the NSF classification: See https://www.nsf.gov/statistics/seind14/index.cfm/chapter-8/tt08-a.html

[64]A person is defined as working at a university in the W-2 data if their highest wage in that year is from a university EIN.

[65]The information on a institution's Carnegie Classification is provided by IPEDS, this is matched to our data by EIN. Some EINs have institutions of several classifications associated with them (for instance, several state university systems report everything in the system on one EIN).

C Appendix: Industry-University Sponsored Research Contract Example (Redacted)

SPONSORED RESEARCH AGREEMENT

THIS SPONSORED RESEARCH AGREEMENT (the ***"Agreement"***) is entered into as of _________, 2020 (the ***"Effective Date"***) by and between [redacted], a [redacted] corporation having its principal place of business at [redacted] (***"Company"***), and _________ University, an education corporation with offices at ______________ (***"Institution"***).

WHEREAS, Company desires that Institution conduct, and Institution desires to conduct, research relating to Company's proprietary [redacted] inhibitor (the ***"Research"***), as described more fully in the research plan attached hereto as ***Exhibit A*** (the ***"Research Plan"***);

WHEREAS, the Research will further Institution's instructional and research objectives in a manner consistent with its status as a non-profit, tax-exempt educational institution; and

WHEREAS, Company and Institution desire to enter into this Agreement under which Company will fund the Research at Institution, and Institution shall grant to Company certain rights with respect to inventions and discoveries of Institution arising from the Research.

NOW, THEREFORE, in consideration of the foregoing premises and the mutual covenants set forth below, and for other good and valuable consideration, receipt of which is hereby acknowledged, Company and Institution agree as follows:

1. SPONSORED RESEARCH. Institution agrees to use reasonable efforts perform the Research described in the Research Plan, as amended from time to time upon mutual written consent of the parties, and will furnish the staff, facilities, know-how, equipment, instruments, supplies and technical skill necessary for performance of the Research. Institution shall use reasonable efforts to perform the Research in full compliance with all applicable laws, rules and regulations and good scientific practices. Nothing contained in this Agreement shall be construed as a warranty on the part of the Institution that any Results or Inventions will be achieved by the Research, or that any Results of Inventions achieved by the Research, if any, are or will be commercially exploitable and furthermore, Institution makes no warranties whatsoever as to the commercial or scientific value of any results which may be achieved in the Research. Institution hereby excludes any and all warranties, implied or express, including warranties of MERCHANTIBILITY or FITNESS FOR A PARTICULAR PURPOSE or of non-infringement of patents or other proprietary rights. Institution and the Principal Investigator shall use reasonable efforts to distinguish the Research performed under this Agreement from other work the Principal Investigator performs for academic and industrial purposes (collectively, ***"Other Work"***), and shall keep records pertaining to such Other Work separately from the records to be maintained pursuant to Section 0

2. PRINCIPAL INVESTIGATOR. The Research is to be conducted by Institution under the direction of Institution employee [redacted PI name] (the ***"Principal Investigator"***). The Principal Investigator is considered essential to the Research being performed, and no substitution may be made without the prior written agreement of Company. If for any reason the Principal Investigator becomes unavailable, or cannot conduct or complete the Research, Institution will propose a successor whose appointment as Principal Investigator shall be subject to the approval of Company. If the parties are unable to agree upon a successor within thirty (30) calendar days after the Principal Investigator ceases his or her involvement in the Research, this Agreement may be terminated by Company pursuant to Section 9.2. Nothing herein contained shall be deemed to impose an obligation on Institution to find a replacement for the Principal Investigator.

3. RESEARCH FUNDING. In consideration of Institution's (including Principal Investigator's) performance of the Research, Company shall pay Institution the maximum sum of $[redacted] (inclusive of all overhead and direct and indirect costs of Research activities) to fund the Research, which shall be payable on the schedule set forth in ***Exhibit B*** hereto. Company shall not be obligated to make any payments to Institution (including, without limitation, any overhead or direct or indirect costs) except as expressly set forth in this Article 0 and ***Exhibit B***, unless the parties otherwise mutually agree in writing. All payments pursuant to this Article 0 shall be by wire transfer or check to such account or address as Institution may specify in writing. The parties agree and acknowledge that the compensation provided under the terms of this Agreement is consistent with the fair market value of the services under the Agreement negotiated in arm's-length transactions, and has not been determined in any manner which takes into account the value or volume of any business generated between the parties, including any of their affiliates.

4. RECORDS; REPORTS.

4.1 Records. Institution shall use reasonable efforts keep complete and accurate financial and scientific records relating to the Research and to maintain such records in accordance with good scientific practices.

4.2 Reports. The Principal Investigator shall submit to Company: (a) oral updates regarding Research activities and Results (as defined herein) on a regular basis, as reasonably agreed upon by the parties; and (b) written reports detailing Research status, activities and Results, including all data and conclusions, at the intervals specified in the Research Plan, but in any event at least once per calendar quarter, within sixty (60) calendar days after the end of the period to which the report relates. The Principal Investigator shall submit to Company a comprehensive final report detailing the Research activities, accomplishments and Results within ninety (90) calendar days after the earlier of: (i) the date the Research is completed, or (ii) the date that this Agreement expires or terminates. The final report will also include a summary, by major cost categories, of expenses directly related to the Research. Company may freely utilize all information submitted or made available to it pursuant to this Article 0 in any manner.

5. PUBLICATION.

5.1 By Institution. Institution is free to publish the Results of the Research conducted hereunder and agrees that any proposed publication will be provided to Company at least thirty (30) calendar days in advance of submission to any publisher or presentation (as applicable). Company shall have the opportunity to review and comment on any proposed manuscripts or the substance of any presentations describing the Research or the Results. The Company shall notify Institution in writing within thirty (30) calendar days of receipt of such draft whether such draft contains Company Confidential Information (which shall be removed from the draft at Company's written request) or information that, if published within thirty (30) calendar days, would have an adverse effect on a patent application in which the Company owns full or part interest. In the latter case, if such draft for publication describes an Invention, or if submission of such manuscript for publication or delivery of such presentation would preclude the Company from obtaining patent protection for patentable Inventions arising from the Research unless an application is filed with relevant patent authorities, Institution shall, at Company's option, either delete the enabling portion of the proposed publication or presentation or withhold publication or delay presentation for up to an additional sixty (60) calendar days until a patent application covering such Invention(s) is completed and filed. Upon Institution's request, Company and Institution shall work in good faith to develop substitute language that is scientifically comparable but does not disclose Company's Confidential Information or the enabling portion of a proposed patent application. For the purpose of this provision only, the term Confidential Information shall not include the data, results, materials, or description of the Research methodology necessary for a meaningful publication, which may otherwise come within the definition of Confidential Information contained in Section 5.

5.2 By Company. Company shall be free to publish or present the Results at its discretion. Company shall acknowledge Institution's and the Principal Investigator's role in the Research in any such publication or presentation and shall include the Principal Investigator as an author, if appropriate, consistent with standard practice for scientific publications.

5.3 Company Technology. Notwithstanding the provisions of Section 0, if any Company Technology (as defined herein) is provided to or generated by Institution for use in connection with the Research or any portion thereof, then in light of the proprietary nature of such Company Technology, the parties agree that Company shall have the first right, in Company's sole discretion, to publish or present Company Technology and, as and to the extent applicable, Company shall acknowledge Institution's and the Principal Investigator's role in the Research in such publication or presentation and shall include the Principal Investigator as an author, if appropriate, consistent with standard practice for scientific publications.

6. CONFIDENTIAL INFORMATION AND MATERIALS.

6.1 Confidentiality and Non-Use of Confidential Information. Confidential Information shall mean all proprietary information of a party (the ***"Disclosing Party"***) that is disclosed to the other party (the ***"Receiving Party"***), in written, oral or other form, as background for or in conjunction with the Research, after the Effective Date and whether such information is provided by the Disclosing Party directly or on the Disclosing Party's behalf by a third party (***"Confidential Information"***); *provided, however,* that all Company Technology shall be deemed Confidential Information of Company, subject to Section 6.2, and the Receiving Party and Disclosing Party with respect to such Company Confidential Information shall be deemed to be Institution and Company, respectively. During the Term and for seven (7) years thereafter, subject to the last sentence of Section 0, the Receiving Party shall:

(a) exercise, and use reasonable efforts to cause its employees, agents and consultants to exercise, reasonable care to hold in confidence and not disclose Confidential Information of the Disclosing Party to third parties or release it for publication or presentation without the prior written consent of the Disclosing Party;

(b) not use, and use reasonable efforts to cause its employees, agents and consultants not to use, Confidential Information of the Disclosing Party for any purpose not expressly contemplated by this Agreement without the prior written consent of the Disclosing Party; and

(c) be responsible for any breach of this Article 0 by any of its employees, agents and consultants.

6.2 Exclusions from Confidentiality and Non-Use Obligations. Confidential Information of a Disclosing Party shall not include any information that the Receiving Party can demonstrate by competent evidence:

(a) was already known to the Receiving Party, other than under an obligation of confidentiality, at the time of disclosure to the Receiving Party by or on behalf of the Disclosing Party, as demonstrated by competent evidence;

(b) was generally available to the public or otherwise part of the public domain at the time of its disclosure to the Receiving Party by or on behalf of the Disclosing Party;

(c) became generally available to the public or otherwise part of the public domain after its disclosure and other than through any act or omission of the Receiving Party in breach of this Agreement;

(d) is independently discovered or developed by the Receiving Party (outside of the Research, in the case of Institution) without the use of Confidential Information of the Disclosing Party, including, without limitation, if Institution is the Receiving Party, any Materials, as demonstrated by competent evidence; or

(e) is disclosed to the Receiving Party, on a non-confidential basis, by a third party who had no obligation to the Disclosing Party not to disclose such information to others.

6.3 Authorized Disclosure. The Receiving Party shall not be prohibited from disclosing Confidential Information to the extent such information is required to be disclosed by court order or by applicable law or government regulation; *provided, however,* that in such event, the Receiving Party shall give reasonable advance notice (except where impracticable) to the Disclosing Party of such required disclosure and, at the Disclosing Party's request and expense, shall cooperate with the Disclosing Party's efforts to contest such disclosure, and/or to obtain a protective order or other confidential treatment of the Confidential Information required to be disclosed.

6.4 Materials. Institution acknowledges that it may receive certain materials, including without limitation chemical, biological and other compounds (collectively, "Materials") from Company or from third parties on Company's behalf for use in performing the Research. Institution shall exercise, and shall use reasonable efforts to cause the Principal Investigator and other employees, agents and consultants of Institution to exercise, reasonable care to use the Company Technology and Materials only for such purpose and shall not transfer or otherwise provide access to the Company Technology or Materials to any person other than the Principal Investigator and other employees, agents and consultants of Institution performing Research hereunder without the prior written consent of Company. Upon conclusion of the Research, Institution shall return to Company or destroy, as directed by Company, all Company Technology including without limitation remaining Materials, except that Institution may retain one copy of the Company Technology that is not Materials solely for archival purposes, and Institution may retain in Confidence any electronic files of Company Technology that is not Materials, each of which are automatically saved pursuant to legal, regulatory or policy requirements. Institution acknowledges that the Materials may have biological or chemical properties that are unpredictable, that they are to be used with prudence and caution and that they are not to be used in humans. Institution shall not commingle the Materials with other materials from any source. Company shall retain ownership of the Materials. THE MATERIALS ARE PROVIDED WITH NO WARRANTIES OF ANY KIND, INCLUDING ANY WARRANTY OF MERCHANTABILITY OR FITNESS FOR A PARTICULAR PURPOSE, OR THAT THEY ARE FREE FROM THE RIGHTFUL CLAIM OF ANY THIRD PARTY, BY WAY OF INFRINGEMENT OR THE LIKE.

7. INTELLECTUAL PROPERTY.

7.1 Definitions. In this Agreement, (a) "Company Technology" shall mean the Materials and any proprietary technology or information relating to such Materials, including without limitation information, inventions and discoveries that, in each case, relate to the identities, structures, composition or activity of such Materials and any method of manufacturing or using such Materials; (b) "Results" shall mean all data, results, information and materials, and all associated intellectual property, that are generated, developed or discovered by Institution, its employees, agents, affiliates or contractors, in conducting the Research, whether in written, graphic or electronic form or contained in any computer database or in any computer readable form; (c) "Inventions" shall mean all ideas, inventions, techniques, improvements and other technology, whether or not patentable, and all associated intellectual property, that are conceived, discovered, developed, or reduced to practice by Institution, its employees, agents, affiliates or contractors in connection with performance of this Agreement or in conducting the Research and that are severable from the Company Technology; (d) "Joint Inventions" shall mean all ideas, inventions, techniques, improvements and other technology, whether or not patentable, and all associated intellectual property, that are conceived, discovered, developed, or reduced to practice jointly by Institution, its employees, agents, affiliates or contractors, on the one hand, and Company, its employees, agents or contractors, on the other hand, in connection with performance of this Agreement or in conducting the Research, and (e) "Company Technology Inventions" shall mean all Inventions and Joint Inventions directed to, covering, based on or derived from the Company Technology and/or the Materials, including without limitation Inventions and Joint Inventions directed to or covering any process, composition of matter, or method of use related to the Materials.

7.2 Ownership and License of Certain Rights.

(a) Company Technology. Institution understands and agrees that the underlying intellectual property rights to any Company Technology that is the subject of the Research are owned solely by Company. Except as may be provided herein, neither Institution nor Principal Investigator shall acquire any rights of any kind whatsoever with respect to any Company Technology as a result of conducting the Research or as a result of this Agreement. Institution agrees not to seek or obtain patent protection directed to or covering Company Technology, including without limitation the Materials, without the prior written consent of Company, which Company may withhold in its sole discretion.

(b) Results. Company shall have and retain all right, title and interest in and to the Results, and Institution hereby assigns to Company all of its right, title and interest in and to the Results. All information regarding the Results shall be Confidential Information of the Company. Company hereby grants to the Institution a limited, non-exclusive, and fully-paid license to use the Results for its internal academic, research and educational purposes.

(c) Institution Inventions. Institution shall have and retain all right, title and interest in and to all Inventions other than Company Technology Inventions ("Institution Inventions"). Institution hereby grants to the Company a non-exclusive, worldwide, fully-paid, irrevocable license, including the right to sublicense through multiple tiers of sublicense, to practice the Institution Inventions for all purposes. To the extent permitted by law and any other conflicting obligations, Institution also grants to the Company an exclusive option to obtain an exclusive license to and under Institution's rights in any such Institution Inventions for which Company elects to bear all patent costs pursuant to Section 7.4, on commercially reasonable terms to be negotiated by the parties in good faith.

(d) Company Technology Inventions. Company shall have and retain all right, title and interest in and to all Company Technology Inventions.

(e) Joint Inventions. Institution and Company shall jointly own all right, title and interest in and to all Joint Inventions other than Company Technology Inventions ("Jointly-Owned Joint Inventions"). To the extent permitted by law and any conflicting obligations, Institution hereby grants to the Company an exclusive option to obtain an exclusive license to and under Institution's rights, title and interest in and to such Jointly-Owned Joint Inventions for all purposes on commercially reasonable terms to be negotiated by the parties in good faith.

(f) Option Period and Option Exercise. The options specified in paragraphs 7.2(c) and (e) above, with respect to any specific Institution Invention or Jointly-Owned Joint Invention, shall extend for a period of six (6) months following the date of written disclosure to Company of such Institution Invention or Jointly-Owned Joint Invention (the "Option Period"). Institution agrees that, during the Option Period for an Institution Invention or Jointly-Owned Joint Invention, and during the applicable Negotiation Period (as defined herein) for such Invention, it shall not offer to any third party the opportunity to obtain a license, or enter into any license with any third party, with respect to such Institution Invention or Jointly-Owned Joint Invention, unless Company expressly rejects in writing its exclusive option set forth herein. Company may exercise the options specified in paragraphs 7.2(c) and (e) above with respect to any Institution Invention or Jointly-Owned Joint Invention by sending written notice of such exercise (the "Option Notice") to Institution at any time during the Option Period with respect to the applicable Institution Invention or Jointly-Owned Join Invention. Upon exercise of such option, Company and Institution shall negotiate in good faith and execute the definitive agreement regarding such exclusive license within ninety (90) calendar days after Company sends the Option Notice to Institution (the "Negotiation Period"). If the parties do not conclude a license agreement prior to the expiration of the applicable Negotiation Period or any extension mutually agreed upon by the parties, Institution may then offer to third parties the opportunity to obtain a license to such Institution Invention or Jointly-Owned Joint Invention; *provided, however,* that, during the nine (9) month period following such expiration of the applicable Negotiation Period, Institution shall not grant any third party a license with respect to such Institution Invention or Jointly-Owned Joint

Invention on terms which in the aggregate are more favorable to such third party than the terms offered by Institution to Company without first offering Company the opportunity to license such Institution Invention or Jointly-Owned Joint Invention on such more favorable terms; and provided further that in such case Company shall have the period of sixty (60) calendar days following receipt of Institution's notice of such more favorable terms to decide to take such a license. Neither any failure by Company to exercise its option with respect to any particular Institution Invention or Jointly-Owned Joint Invention, nor any failure of the parties to enter into a license agreement with respect to any particular Institution Invention or Jointly-Owned Joint Invention, shall be deemed a waiver of Company's option with respect to any other Institution Invention or Jointly-Owned Joint Invention.

(g) Execution of Documents; Assistance. Institution agrees promptly to execute such documents and perform such other acts as the Company may reasonably request to obtain, perfect and enforce Company's rights to the Company Technology, Results, Inventions, Joint Inventions, and Company Technology Inventions set forth above. Institution shall require that any employee, agent, affiliate or contractor of Institution that receives or uses the Company Technology, including without limitation the Materials, as permitted herein or performs any aspect of the Research shall agree to assign, and shall assign, to Institution all of his/her/its right, title and interest in and to the Company Technology, Results, Institution Inventions, Joint Inventions and Company Technology Inventions, such that Institution is able to satisfy its obligations to Company hereunder. Each party further agrees to assist the other party in obtaining and enforcing patents and other intellectual property rights and protections relating to Company Technology, Results, Institution Inventions and Joint Inventions in all countries.

7.3 Disclosure of Inventions. Within thirty (30) days of the Executive Director of the Office of Industrial Liaison/Technology Transfer at Institution becoming aware or reasonably believing that an Institution Invention, Joint Invention or Company Technology Invention has been made hereunder, Institution shall disclose such invention in writing to Company in sufficient detail to allow Company to evaluate its significance.

7.4 Patent Prosecution.

(a) Institution Inventions. Institution shall have the first right to prosecute patent applications covering any Institution Invention. Within sixty (60) calendar days after written disclosure of an Institution Invention to Company, Company shall notify Institution in writing if it wants the Institution to pursue patent protection for such Institution Invention. Institution shall then prepare, file and prosecute patent applications as requested by Company to protect such Institution Invention. Company shall bear all reasonable expenses incurred by Institution, in connection with such preparation, filing, prosecution and maintenance of patent applications claiming such Institution Invention. Institution shall have the right but not the obligation, to assume responsibility for making decisions regarding the scope and content of such applications and the prosecution thereof subject to Company's right to review and comment on the draft patent application prior to filing, such comments to be considered in good faith by Institution. Company, however, shall have the right to discontinue the financial support of the prosecution or maintenance of any such patent or patent application upon thirty (30) calendar days' written notice to Institution. If Company elects not to bear all reasonable expenses in connection with the preparation, filing prosecution and maintenance of patent applications claiming an Institution Invention, or otherwise discontinues the financial support of the prosecution or maintenance of any such patent or patent applications claiming such Institution Invention, such Institution Invention shall not be subject to the option set forth in Section 7.2, and Company shall have no rights thereto.

(b) Joint Inventions. Company shall have the first right to prosecute patent applications covering any Joint Invention at its own expense. If Company fails to file a patent application to protect a Joint Invention within ninety (90) calendar days after written disclosure of such Joint Invention to Company, Institution shall be free to file, prosecute or maintain any patents covering such Joint Invention at its own expense. If Company fails to file a patent application on a Joint Invention as set forth above, or elects not to bear all reasonable expenses in connection with the preparation, filing, prosecution and maintenance of patent applications claiming such Joint Invention, or otherwise elects to discontinue the financial support or the prosecution or maintenance of any such patent or patent applications claiming such Joint Invention, such Joint Invention shall not be subject to the option set forth in Section 7.2, and Company shall have no rights thereto.

(c) Company Technology Inventions. Company shall have the sole right (but not the obligation) to prosecute patent applications covering any Company Technology Inventions.

8. INDEMNIFICATION.

8.1 Indemnification by Company. Company agrees to indemnify, defend and hold harmless Institution, its officers, trustees, employees and agents (collectively, the ***"Institution Indemnitees"***) from and against any and all liability, loss, costs (including reasonable attorneys' fees) and damages (collectively, ***"Losses"***) that any such Institution Indemnitee may suffer as the result of third party claims, demands, or judgments against such Institution Indemnitee arising out of (i) Institution's conduct of the Research; (ii) Company's use of the information supplied pursuant to Article 4, and Company's use, disposition or commercialization of any Invention or any intellectual property rights granted to Company hereunder; or (iii) any failure of Company to meet its obligations under this Agreement; except, in each case, to the extent that any such claim, demand, cost or judgment arises from the negligence, recklessness or willful misconduct on the part of any Institution Indemnitee.

8.2 Responsibility of Institution. Institution shall be solely responsible for its acts or omissions and the acts or omissions of the Institution Indemnitees in the performance of the Research hereunder.

8.3 General Conditions of Indemnification. Company's agreement to indemnify, defend and hold harmless Institution and the Indemnitees is conditioned upon Institution: (a) providing written notice to Company of any claim, demand or action arising out of the indemnified activities within thirty (30) calendar days after Institution has knowledge of such claim, demand or action, provided, however, that failure to do so does not relieve Company of its indemnification obligations hereunder, except to the extent Company has been materially prejudiced; (b) permitting Company to assume full responsibility and authority to investigate, prepare for and defend against any such claim or demand, provided that Company shall not agree to any settlement that requires an admission of fault by an Institution Indemnitee without the prior written consent of Institution; (c) reasonably assisting Company, at Company's reasonable expense, in the investigation of, preparation for and defense of any such claim or demand; and (d) not compromising or settling such claim or demand without Company's written consent.

9. TERM; TERMINATION.

9.1 Term of Agreement. The term of this Agreement shall begin on the Effective Date and, unless this Agreement is earlier terminated pursuant to this Article 9, shall continue until the date that is the later of: (i) two (2) years after the Effective Date, or (ii) the date that the Research is completed (the ***"Term"***).

9.2 Termination by Company. Company may terminate this Agreement either (a) upon thirty (30) calendar days' prior written notice to Institution in the event Company and Institution are unable to agree upon a suitable replacement for the Principal Investigator pursuant to Article 0, or (b) for any reason or for no reason upon sixty (60) calendar days' prior written notice to Institution.

9.3 Termination by Institution. Institution may terminate this Agreement upon forty-five (45) calendar days' prior written notice to Company in the event Company materially breaches this Agreement and fails to cure such breach before expiration of such 45-day notice period.

9.4 Effects of Termination. Termination of this Agreement shall not affect the rights and obligations of the parties that accrued prior to the effective date of such termination, including, without limitation, Institution's right to receive, and Company's obligation to pay, amounts due under this Agreement with respect to work completed and for non-cancellable obligations incurred prior to such termination. In the event of any termination of this Agreement prior to the expiration date set forth herein, Company shall pay the reasonable costs incurred by Institution in winding down and terminating the Research, including the reasonable costs of the Research during the wind-down period and all reasonable and documented costs and non-cancelable commitments made in accordance with the Research Plan prior to termination. After termination, Institution will submit a final report of all costs incurred and all funds received under this Agreement as set forth in Section 0. The report shall be accompanied by a check for any funds remaining which were paid to Institution under Article 0 with respect to Research Plan activities not performed by Institution, if any, after allowable costs and non-cancelable commitments have been paid.

9.5 Survival. The provisions of Sections 4.2, 6.1 – 6.3, 9.4 and 9.5 and Articles 0, 0, 0, **Error! Reference source not found.**, and 10 shall survive termination or expiration of this Agreement.

10. MISCELLANEOUS.

10.1 Relationship of Parties. The relationship between the parties is that of independent contractors, and neither party shall have the authority to bind or act on behalf of the other party. This Agreement shall not constitute, create, or in any way be interpreted as a joint venture, partnership or business organization of any kind.

10.2 Use of Other Party's Name. Each party agrees that it will not under any circumstance use the name of the other party or its employees in any advertisement, press release or publicity with reference to this Agreement without prior written approval of the other party, except as required by law.

10.3 No Implied Licenses. Except as expressly set forth in this Agreement, nothing in this Agreement shall be construed as conferring on either party an express or implied license, option to license, or other right with respect to, any technology, information, patent application, patent or intellectual property rights of the other party.

10.4 Choice of Law. This Agreement shall be governed by the laws of the State of New York, excluding its conflicts of laws principles.

10.5 Entire Agreement. This Agreement, together with all Exhibits attached hereto and hereby incorporated herein, constitutes the final, complete and exclusive agreement of the parties with respect to the subject matter hereof and supersedes all prior understandings and agreements relating to its subject matter. This Agreement may not be changed, modified, amended or supplemented except by a written instrument signed by an authorized representative of each party.

10.6 Assignment; Delegation. Neither party may assign this Agreement without the prior written consent of the other party; *provided, however,* that Company may assign this Agreement without Institution's consent (a) in connection with the transfer or sale of all or substantially all of the business of Company to which this Agreement relates, whether by merger, sale of stock, sale of assets or otherwise, or (b) to an affiliate of Company, provided that Company shall promptly provide written notice of such assignment to Institution within ten (10) business days post execution. Any attempted assignment of this Agreement not in compliance with this Section 10.6 shall be null and void. No assignment shall relieve either party of the performance of any accrued obligation that such party may then have under this Agreement. This Agreement shall inure to the benefit of and be binding upon each party signatory hereto, its successors and permitted assigns, subsidiaries and affiliates. Institution may not delegate or subcontract any of its obligations under this Agreement to any third party, except upon Company's prior written consent (which Company may withhold in its sole discretion). Institution shall at all times be responsible for the payment of its permitted delegatees and subcontractors, and for the compliance of its permitted delegatees and subcontractors with the terms and conditions of this Agreement.

10.7 Severability. If any provision of this Agreement is found by a court of competent jurisdiction to be unenforceable, then such provision will be construed, to the extent feasible, so as to render the provision enforceable, and if no feasible interpretation would save such provision, it will be severed from the remainder of this Agreement. The remainder of this Agreement will remain in full force and effect, unless the severed provision is essential and material to the rights or benefits received by either party. In such event, the parties will negotiate, in good faith, and substitute a valid and enforceable provision or agreement that most nearly implements the parties' intent in entering into this Agreement.

10.8 Notices. Any notices required or permitted hereunder shall be given to the appropriate party at the address specified below or at such other address as the party shall specify in writing. Such notice shall be deemed given upon personal delivery, or upon receipt by certified or registered mail, postage prepaid, or upon receipt by Federal Express or an equivalent overnight delivery.

If to Company: [redacted]

With a copy to: [redacted]

If to Institution:

With a copy to:

And to PI:

All notices shall be deemed made upon receipt by the addressee as evidenced by the applicable written receipt or, in the case of a facsimile, as evidenced by the confirmation of transmission.

10.9 Non-Waiver; Force Majeure. No failure or delay of one of the parties to insist upon strict performance of any of its rights or powers under this Agreement shall operate as a waiver thereof, nor shall any other single or partial exercise of such right or power preclude any other further exercise of any rights or remedies provided by law. Neither party shall be liable for any failure to perform as required by this Agreement to the extent such failure to perform is due to circumstances reasonably beyond such party's control, including, without limitation, labor disturbances, or labor disputes of any kind, accident, failure to obtain any governmental approval required for full performance, civil disorders or commotions, acts of aggression or terrorism, acts of God, energy other conservation measures imposed by law or regulation, explosions, failure of utilities, mechanical breakdowns, material shortages, disease, or other such occurrences.

10.10 English Language. This Agreement has been prepared in the English language, and the English language shall control its interpretation.

10.11 Counterparts. This Agreement may be executed in counterparts, each of which shall be deemed an original, but all of which together shall constitute one and the same instrument.

[Signature page follows]

IN WITNESS WHEREOF, the parties have executed this Agreement as of the date and year first above written.

COMPANY	**UNIVERSITY**
By:______________________________	By:____________________________________
Name:____________________________	Name:__________________________________
Title:_____________________________	Title:___________________________________

As Principal Investigator under this Agreement, I attest that I have read this Agreement in its entirety, that I consent to the terms hereof, and that I shall use my best efforts to perform my obligations and responsibilities hereunder:

By:______________________________
[redacted PI name]
Principal Investigator

EXHIBIT A

Research Plan

EXHIBIT B

Schedule of Payments

Payment Due Date	Amount of Payment