CUTTING THE INNOVATION ENGINE: HOW FEDERAL FUNDING SHOCKS AFFECT UNIVERSITY PATENTING, ENTREPRENEURSHIP, AND PUBLICATIONS*

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This article 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 preexisting 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, whereas 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

*This article previously circulated as "The Color of Money: Federal vs. Industry Funding of University Research." We are grateful to the editor, Stefanie Stantcheva, and five anonymous referees for detailed and thoughtful suggestions. We thank Pierre Azoulay, Sharon Belenzon, Lauren Cohen, Daniel Gross, Hans Hvide, Danielle Li, Scott Kominers, Natsuko Nicholls, Jason Owen-Smith, Stefanie Stantcheva, and Beth Uberseder, as well as participants at AEA, NBER Productivity, Innovation and Entrepreneurship, NBER SI Science of Science, NBER SI Labor Studies/Education, NYU, MIT, APPAM, EPFL Innovation Seminar, the virtual Finance in the Cloud conference, the NSF SI Future of IP conference, the AIEA seminar series, and SEA. For helpful research assistance, we thank Belinda Chen and Jun Wong. Howell's research on this project was funded by the NBER Science of Science Program, sponsored by the Sloan Foundation (G-2018-10066), and by the Kauffman Foundation (G-2020004-8367). This article uses data from the U.S. Census Bureau. Any views expressed are those of the authors and not those of the U.S. Census Bureau. The Census Bureau's Disclosure Review Board and Disclosure Avoidance Officers have reviewed this data product for unauthorized disclosure of confidential information and have approved the disclosure avoidance practices applied to this release (DRB Approval Numbers CBDRB-FY20-152, CBDRB-FY20-CES009-004, CBDRB-FY20-CES009-006, CBDRB-FY21-CES009-007, CBDRB-FY21-CES007-008, CBDRB-FY22-CES17-002, CBDRB-FY22-CES007-009, and CBDRB-FY22-CES007-010; DMS number 7507193).

The Quarterly Journal of Economics (2023), 895–954. https://doi.org/10.1093/qje/qjac046.
Advance Access publication on January 9, 2023.

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. *JEL Codes:* O3, G18, G38, I2.

I. Introduction

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 I). 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 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, the 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 W-2 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 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 preexisting 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

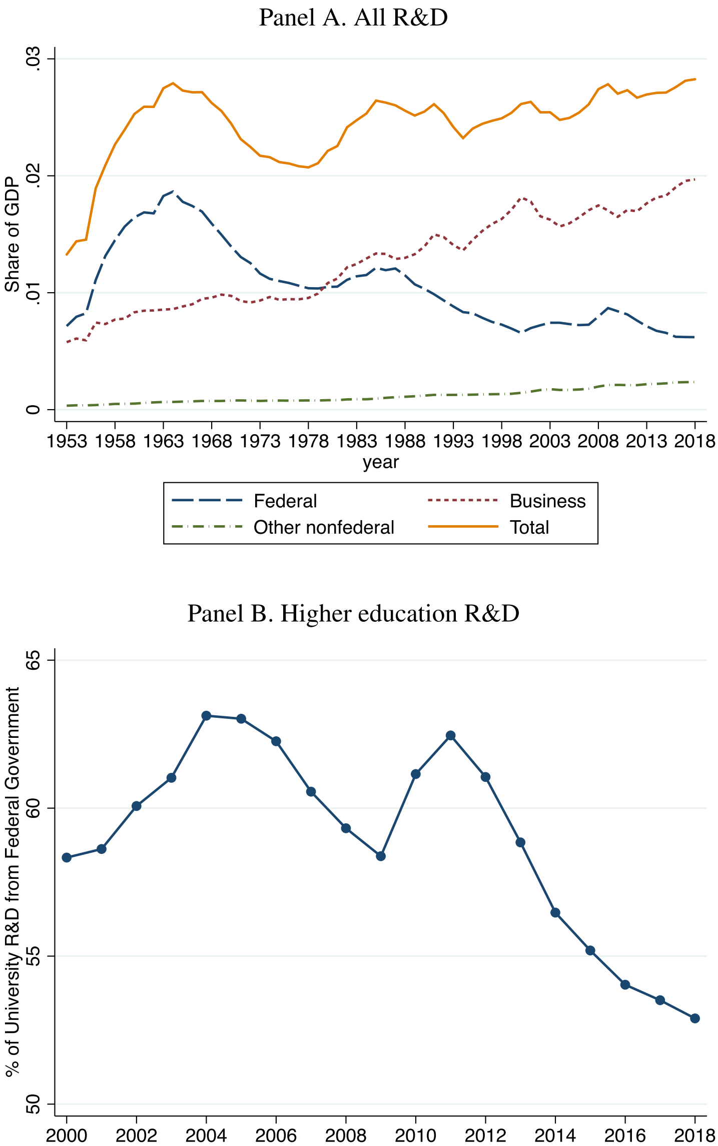

FIGURE I

Sources of U.S. Research Funding, 2000–2018

Panel A shows the percent of total U.S. R&D spending by source of funds. Panel B 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.

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 effect on individual researcher funding and thus have scope to affect the innovation outputs of academic research.

In a difference-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 pretrends 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 trade-offs 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 toward being useful in the economy and academia.

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 pretrends—supporting the identification assumption—and indicates a striking downward trend after the shock. The effect is strongest for graduate students and postdocs, which is intuitive because they have the requisite skills and experience to found a high-tech startup and are in a transitional stage in their career. Anecdotally, graduate students and postdocs are responsible for the majority of university commercialization (Lerner, Stein, and Williams 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 to 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 more citations, and are in higher-impact journals.[1]

We expect that researchers whose existing funding is closer to expiring will be most exposed to the shocks because they are more likely to need new funding. Indeed, all 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 the 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 pretrends 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'

1. Across all three innovation outcomes, we find no effects among research staff. Including staff—who are 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 affected 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 National Institutes of Health funding increases publication quantity and quality, Myers (2020) and Byrski, Gaessler, and Higgins (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).

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 propose three nonmutually 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 fewer resources are available to conduct research and innovation. Second, the decline in federal funding could decrease 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 channels may be at play to some degree, but the strong positive effect on patenting is evidence against a pure productivity story, and the large negative effect on high-tech entrepreneurship is evidence against a pure basic-versus-applied story. The results are best aligned with the final channel, where a shift away from federal and toward private funding affects outputs because the two sources have contrasting contractual and incentive structures that alter researchers' objectives and constraints (Azoulay and Li 2020). Although federal awards typically assert no property rights to research outcomes, private firms have incentives to appropriate research outputs and, for that reason, use complex legal contracts with researchers. This could lead research to be commercialized more often 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 represents 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. Furthermore, 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 by university researchers, who are free to use the intellectual property (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 (Government-University-Industry Research Roundtable and Industrial Research Institute 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 article is to show that federal funding is important for creating open, impactful innovations and enabling researchers to take these innovations to startups. Science that is more open 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 research findings could generalize to broader reductions in federal funding and point to long-term implications for economic growth.

We contribute to three branches of literature, all of which are relevant to policy. The first concerns how funding availability affects innovation and entrepreneurship (Hall and Lerner 2010; Kerr and Nanda 2011). 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, Bernstein, and Mezzanotti forthcoming). We find that following federal funding cuts, university researcher entrepreneurship declines while patenting increases, pointing to substitution with private funding.

The second branch of literature addresses the tension between IP 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, Cho, and Cohen 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). Thus, funding science publicly may lead to more benefits than private funding (Budish, Roin, and Williams 2015; Azoulay et al. 2019). 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 article 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; Babina et al. 2021; 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 agencies 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, Henderson, and Jaffe (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.

II. Data and Sample Overview

We use rich administrative data from multiple sources to understand how federal funding availability affects university researchers' innovation outputs, including high-tech startup formation, patents, and publications. This section summarizes the data

3. Also see Belenzon and Schankerman (2009); Foray and Lissoni (2010); and Åstebro, Bazzazian, and Braguinsky (2012).

4. There is a related, nascent literature comparing public and private funding. Working papers on this topic include Guerzoni et al. (2014) and Kong et al. (2020). One related paper that also uses UMETRICS database is Glennon, Lane, and Sodhi (2018). It examines 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. This article 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 preexisting 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 federal versus private funders affects research outcomes.

that we use in the analysis. A comprehensive description is in Online 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 2001–2017. The data include grant expenditures by employee-year and other grant details including the funder's name. We further observe each researcher's occupation (faculty, graduate student/postdoc/research scientist, undergraduate student, or staff) and department (e.g., physics or biology). We construct a balanced panel of researchers for 2001–2017, with researchers observed both before and after they are paid on a grant in the UMETRICS data. Table I, Panel A reports summary statistics for key variables using the individual-year panel we use in the main analysis, which contains about 18,000 individuals (see Section III for sample restrictions). Among the researchers, 16.4% are faculty; 43.2% are graduate students, postdocs, 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 CFDA codes and funder names to determine whether the funder is a federal government agency, a private firm, or other source (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 in narrow fields that form the basis of our empirical strategy described in Section III. Each CFDA program is related to a specific field of research. Two examples are "Cardiovascular Diseases Research," and "Agricultural Basic and Applied Research" (see be-

5. The universities in our sample from the 2018 q4 UMETRICS release are the University of Arizona, Boston University, the University of Cincinnati, Emory University, the University of Hawaii, Indiana University, the University of Iowa, the University of Michigan, Michigan State University, the University of Missouri, New York University, Northwestern University, the University of Pennsylvania, Penn State University, the University of Pittsburgh, Princeton University, Purdue, Stony Brook University, the University of Texas at Austin, the University of Virginia, Washington University in St Louis, and the 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 (see Section III for our further sample restrictions). For more information, see https://www.govinfo.gov/app/details/CFR-2014-title2-vol1/CFR-2014-title2-vol1-sec200-10/summary.

TABLE I
SUMMARY STATISTICS

	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

TABLE I
CONTINUED

	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

TABLE I
CONTINUED

	Number of observations	Mean	Standard deviation
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	

Notes. Panel A shows summary statistics for the UMETRICS sample, Panel B for the patent data, Panel C for publications data matched to the UMETRICS sample, and Panel D for the restricted-use U.S. 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 the 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 nonprofits). 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 a 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.

low for more examples). We obtain aggregate federal funding at the CFDA program level from the Federal Audit Clearinghouse. As Table I, 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 I, 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 undergraduates receive some private funding.[7] Online Appendix 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 V) in explaining our main results presented in Section IV.

We use three measures of patenting activity based on the patent application year, described in Table I, Panel B. 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 postdocs (0.28%), and much smaller for undergraduates (0.07%) and staff (0.06%) who do not generally 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 Online Appendix B), which is higher 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 Table I, Panel C. The IRIS UMETRICS program matched researchers to PubMed publica-

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

tions 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 the Microsoft Academic Graph database. 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) the 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 Table I, Panel D 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 is a high-tech entrepreneur in a given year is about 0.23%, which, as we explain

8. IRIS has only matched PubMed data. Because individuals are deidentified 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.

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, and 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]

III. 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:

i. They are largely uncorrelated with the characteristics of individual researchers;
ii. They are likely to be idiosyncratic rather than reflecting technological trends;

11. In unreported analysis, we considered employment at older incumbent firms but find no consistent effects.

12. In Section IV.D, we show that positive shocks yield symmetric but noisier results.

iii. They do not require imposing a lag structure on the relationship between shocks and outcomes;
iv. They permit visual event studies and testing for pretrends;
v. They are policy relevant.

Before expanding on these points, 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: (i) the total amount of federal funding in the field (i.e., at the CFDA level) falls by at least 40% from the previous year; (ii) the decline in funding is temporary and the funding level reverts back to the preshock level at some later point; and (iii) there are no large positive or negative funding changes ($>$ 30% or $<$ –30%) 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; she 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. Online Appendix B.2 provides more details about the CFDA data and spending shocks. Table I describes the summary statistics based on this sample.

III.A. Estimating Equation

To estimate the effect of negative funding shocks on research outcomes, we use difference-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 PI, d the department, u the university, and t the year:

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

The unit of observation is the individual-year. The coefficient of interest, β, is an indicator for the year being postshock. 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 pretrends and to understand the timing of any effects, we estimate the following dynamic event study version of equation (1):

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

The vector $\boldsymbol{D}_{i,\tau}$ 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.

III.B. 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.

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 variation over time 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.

First, changes in the aggregate supply of federal funding in 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 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 Online 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 Online 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 our having identified reasonably idiosyncratic events.

We combine the shocks into a single event study in Figure II. It plots the log level of funding for CFDA codes that experience negative shocks around the year of our large federal funding

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

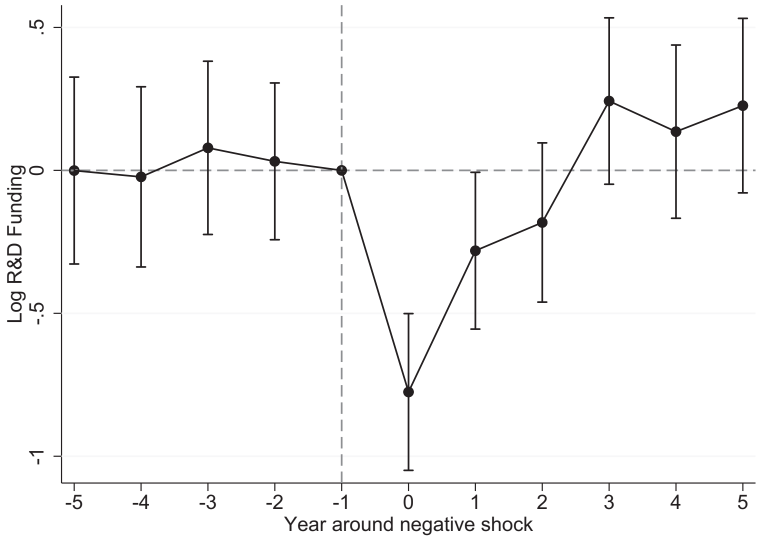

FIGURE II

Aggregate Funding of Research Expenditure from Federal Grants around Shocks

This figure shows that large, negative shocks at the CFDA program-level are temporary and without pretrends. 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.

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 preshock level less than three years after the shock. Importantly, there is no consistent pretrend before the shock.[19] This offers strong evidence

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 difference-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 II, we use –1 normalized to zero 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 pretrend. Our restriction of no other large (> 30%) changes in the two-year

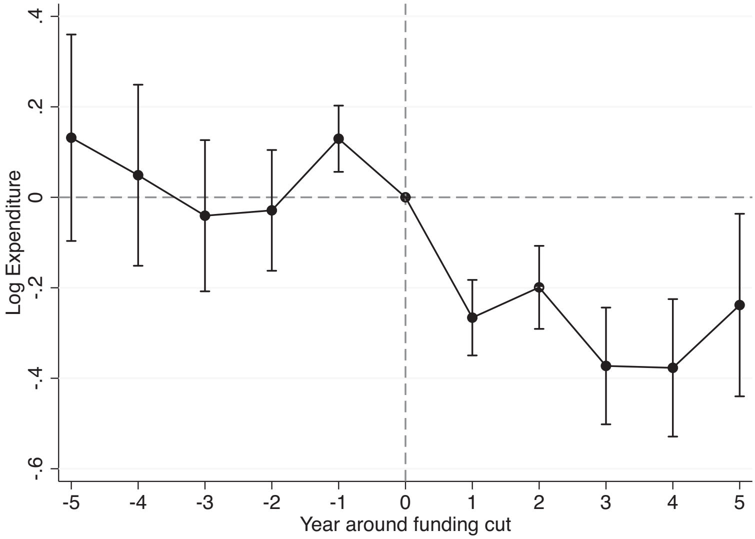

FIGURE III

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.

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 II displays the first necessary variation for our empirical strategy. The second necessary variation is shown in Figure III, 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

period before the identified shock permits pretrends over time in which no year-to-year change exceeds 30%, or large shocks in years outside the two-year preperiod.

grants are multiyear, but the negative effect in Figure III reflects "compliers" who need new funding after the year of the shock. Although it may be feasible for some researchers to wait and apply for new funding during the years after 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 article, 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. Although this assumption is fundamentally untestable, Figure III shows no evidence of pretrends 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 in Online Appendix Table A.1, in which 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 II, column (1). After the shock, federally funded expenditure of the affected researchers 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 explains the results, then we should also observe effects beyond university researchers in the overall field, where private investment dominates and federal research fund-

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

21. Where $-28\% = e^{-0.3275} - 1$, where –0.3275 is the coefficient on "log Federal funding" in column (1) of Table II.

TABLE II

THE EFFECTS OF FEDERAL FUNDING CUTS ON HIGH-TECH ENTREPRENEURSHIP, PATENTS, AND PUBLICATIONS

Dependent variable	Log federal funding$_{i,t}$ (1)	High-tech entrepreneurship$_{i,t}$ (2)	Any patents$_{i,t}$ (3)	Number of patents$_{i,t}$ (4)	Any publications$_{i,t}$ (5)	Number of publications$_{i,t}$ (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×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	0.0023	0.0023	0.0028	0.097	0.302

Notes. This table reports changes in high-tech entrepreneurship, patents, 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 the 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 III. 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.

ing plays a small role. We show in Section IV.D 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.

IV. 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. We then focus on which researcher occupations drive these results and examine heterogeneity in the quality of patents and publications. Finally, we present robustness tests.

IV.A. 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 trade-offs in how innovation outputs are appropriated and disseminated. They can be appropriated and commercialized by the researcher herself in a new startup, they can be patented and thus made contractable across firms and institutions, or they can be 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 II, 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 (Table I, Panel A), 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 IV. 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 pretrends in the event study, again supporting the identification assumption.

We explore other career trajectories in Online 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 majority 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 ar-

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, high-tech sectors represent roughly 15% of employment (Babina and Howell forthcoming). Therefore, high-tech entrepreneurship rates are likely lower among workers of incumbent firms than in our sample of academic employment.

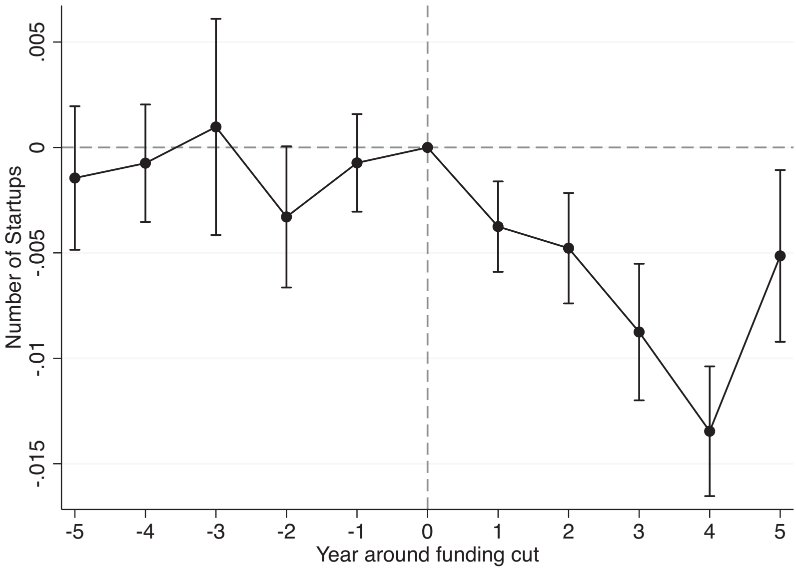

FIGURE IV

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 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.

ticle, 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 contractable intellectual property; alternatives are to publish the invention as openly available science or to maintain it as a trade secret. In contrast to high-tech entrepreneurship, Table II 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 particular year. This is economically large because the base chance of having a granted patent in our sample is high compared 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 overall U.S. population is 0.21%.[26] Bell et al. (2019) point out that

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

24. See the NSF example here: https://www.nsf.gov/awardsearch/showAward?AWD_ID=2025170.

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

26. This is from their intergenerational sample of U.S. citizens born in 1980–84 matched to their parents in the tax data and linked to patent applications. They have 34,973 inventors and 16,360,910 noninventors (Table 1 of their paper).

applying for a patent is a compelling outcome to study because, despite being rare, it is important for economic growth.

Figure V reports the event study estimates for the patent outcomes. These indicate no pretrends 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 granting 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, Jaffe, and Raiteri (2019). In Section V, 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 II, 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 Online 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, they would imply that the average shock (from our data) would lead to around 1,000 fewer high-tech startups in that year from university researchers in the United States, which is 2.4% of the total average number

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 at https://www.uspto.gov/web/offices/ac/ido/oeip/taf/us_stat.htm.

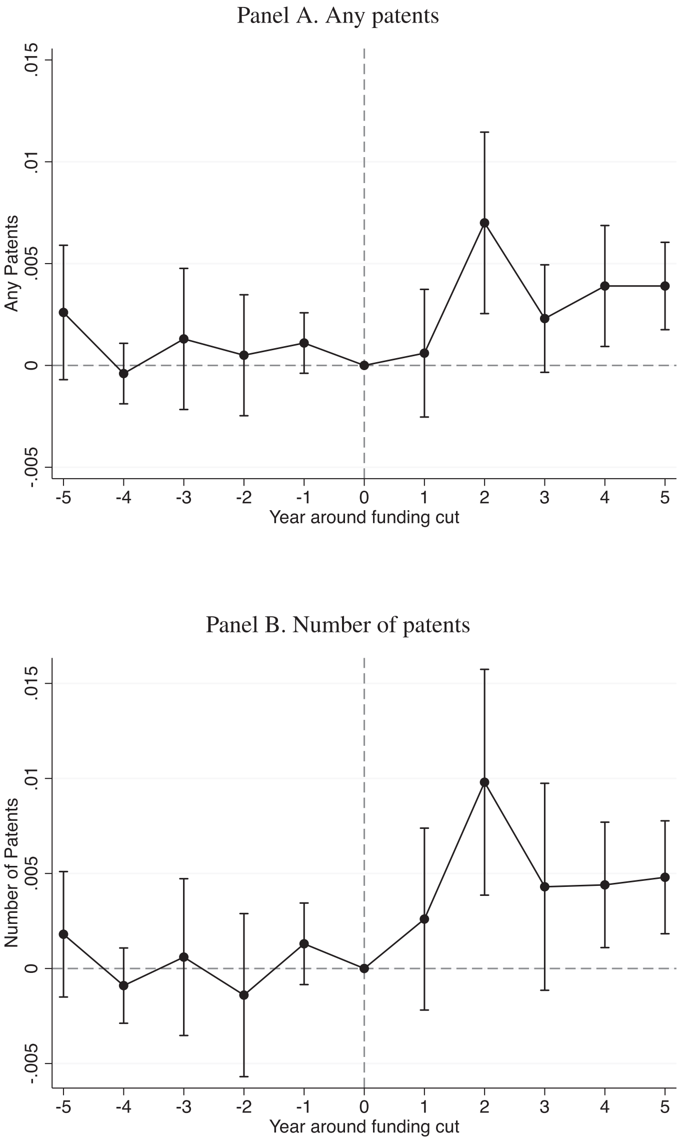

FIGURE V

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.

of annual new high-tech startups in the United States 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]

IV.B. Effects by Occupation

Our data include four types of researchers: faculty, graduate students and postdocs, 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 III. 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 postdocs (column (2)). This group has the highest propensity for high-tech entrepreneurship, 0.25%, as these researchers have 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 consider patents in Table III, Panel B. The positive average effect is driven by faculty and graduate students/postdocs (columns (1) and (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 for 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

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 in 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 U.S. universities (according to NSF IPEDS data). We estimate $\frac{0.0018\times 86{,}000}{0.15} = 1{,}032$ fewer high-tech startups, $\frac{0.0039\times 86{,}000}{0.15} = 2{,}236$ additional patents, and $\frac{0.0466\times 86{,}000}{0.15} = 26{,}717$ fewer publications.

TABLE III

THE EFFECTS OF FEDERAL FUNDING CUTS ON HIGH-TECH ENTREPRENEURSHIP, PATENTS, AND PUBLICATIONS BY OCCUPATION

Occupational group	Faculty (1)	Graduate students and postdocs (2)	Undergraduate students (3)	Staff (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

TABLE III
CONTINUED

Occupational group	Faculty (1)	Graduate students and postdocs (2)	Undergraduate students (3)	Staff (4)
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

Notes. 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 heterogeneous changes in researchers' outcomes are shown by occupation: faculty (column (1)), graduate students and 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 the 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 III. 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.

see a strong, negative effect. This also accords with intuition because faculty have stable academic careers in which they will author many academic papers, whereas other researchers are, even without funding shocks, likely to move on to other careers. Thus, while graduate students and postdocs drive outcomes related to private-sector employment, this measures the long-run effects on an academic 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 or the trajectory of output commercialization or dissemination. Their outputs could, however, be affected by funding levels through other channels, so we include them in our main analysis.[28]

IV.C. 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 VI, 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 IV, columns (1) and (2), are consistent with these event study analyses. Second, we consider citations, which measure impact on future innovation

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 from splitting the sample by startup growth characteristics.

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

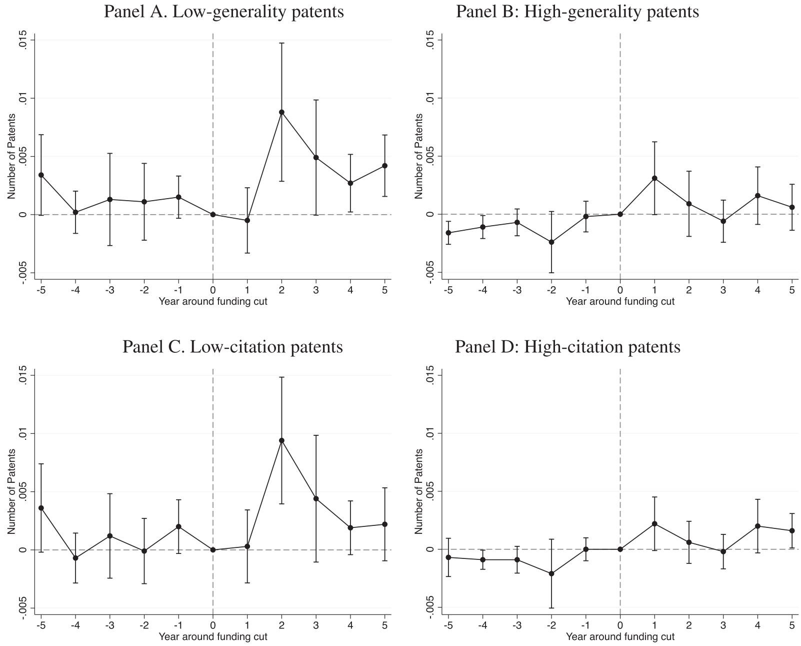

FIGURE VI

Heterogeneity in the 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.

and thus are a proxy for knowledge spillovers. Figure VI, Panels C and D show that the average effect is largely driven by low-citation patents. Table IV, columns (3) and (4) confirm that the coefficient is larger for patents with below-median citations.

Table IV, column (5) 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 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 V. 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 VII, 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 citations 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-citation publications (Table V, column (4)). This is again visible in the figure, where there is no measurable effect for low-citation publications, but a noticeable discontinuity for high-citation publications (Figure VII, 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, 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 V, columns (5) and (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.

TABLE IV

HETEROGENEOUS EFFECTS OF FEDERAL FUNDING CUTS ON PATENTS BY TYPE

Dependent variable	Number of patents$_{i,t}$				
	Low generality (1)	High generality (2)	Low citations (3)	High citations (4)	Private assignee (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×year×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

Notes. This table reports changes in patent outcomes across a 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 the UMETRICS data. The dependent variable is the number of patents by a person in a given year: column (1) focuses on patents with low generality and column (2) on high-generality patents (high- versus 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-citation patents (high-citation 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 III. 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.

TABLE V
HETEROGENEOUS EFFECTS OF FEDERAL FUNDING CUTS ON PUBLICATIONS BY TYPE

Dependent variable	Number of publications$_{i,t}$						
	Low-impact journal (1)	High-impact journal (2)	Low citations (3)	High citations (4)	Applied (5)	Basic (6)	Cited by patents (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×year×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

Notes. This table reports changes in publication outcomes across a 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 the UMETRICS data. The dependent variable is the number of publications by a person in a given year: column (1) focuses on publications in low-impact journals and column (2) on high-impact journals (the split into high- versus 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-citation publications (the split into high versus 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 versus 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 III. 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.

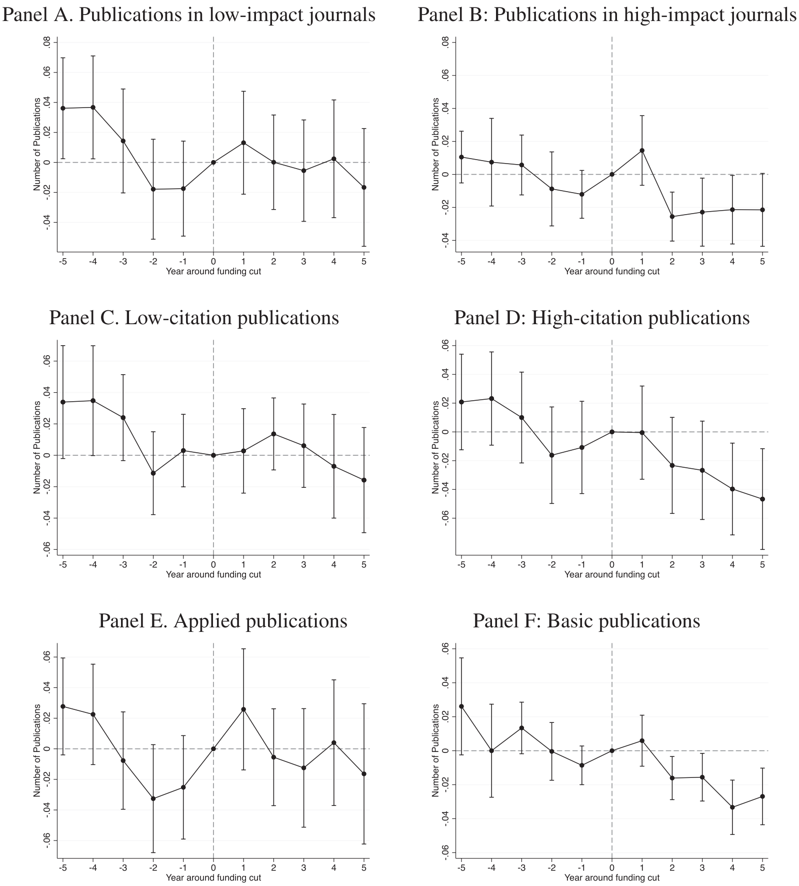

FIGURE VII

Heterogeneity in the Effect of Federal Funding Shocks on the 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 the 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 the 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 that 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.

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

IV.D. 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.

1. *Technological Opportunities.* A key threat to identification is that the large shocks we use 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, they should be associated with fewer rather than more patents. In addition to these points, we present interview and case study evidence in Online 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 provide additional evidence that technological changes are not driving the federal funding cuts used in our main analysis. Most important, we conduct falsification tests in which 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 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 specific year if a researcher from the main sample is shocked in that year and 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 VIII, 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 pretrends and no change postshock, with 95% confidence bounds well outside those of our main effect, supporting the assumption that the shocks are idiosyncratic.

Using the same intuition, we 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

31. The LBD includes all nonfarm, private business activity. We define industry as a six-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.

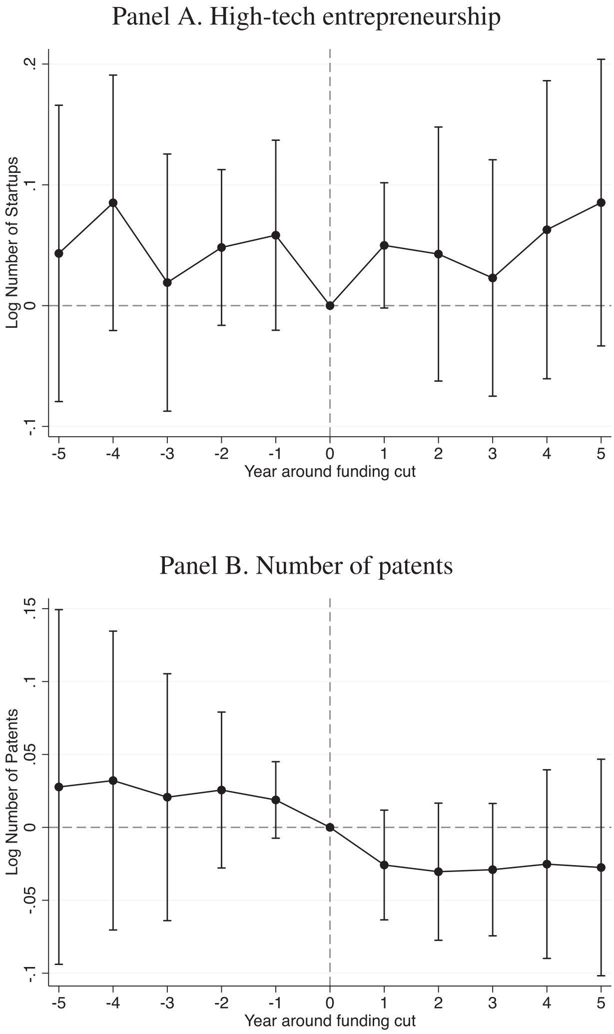

FIGURE VIII

Placebo Test for the Association between CFDA Large Shocks and Aggregate Outcomes

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 six-digit NAICS industry-years where we observe treated (hit by federal funding cuts in narrow CFDA programs) UMETRICS individuals founding high-tech startups after experiencing a funding shock. This model includes industry fixed effects (six-digit NAICS) and year fixed effects. Panel B conducts 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 IV.D for more details.

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 VIII, Panel B shows no evidence of a pretrend or postshock 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.

2. *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 term, 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 versus $\geqslant 2$ years ago).[33] The results are in Table VI. Column (1) shows that the shocks reduce federal expenditure by more than twice as much among the group with older awards, consistent with their 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) and (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) and (6) show that the effects on publications are also larger for researchers without recent federal awards. The differences are statistically significant at the 10% level except for

32. For example, suppose 50 researchers have patents in a patent class, and among those researchers, 20 have a main CFDA code A, 15 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 the 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.

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 expenditures 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.

TABLE VI

THE EFFECTS OF FEDERAL FUNDING CUTS ON HIGH-TECH ENTREPRENEURSHIP, PATENTS, AND PUBLICATIONS BY EX ANTE RESEARCH GRANT TIMING

Dependent variable	Log federal funding$_{i,t}$ (1)	High-tech entrepreneurship$_{i,t}$ (2)	Any patents$_{i,t}$ (3)	Number of patents$_{i,t}$ (4)	Any publications$_{i,t}$ (5)	Number of publications$_{i,t}$ (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 ⩾ 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×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	0.727	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	.020	.073	.091	.024	.365	.477

Notes. This table reports changes in high-tech entrepreneurship, patents, 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 the 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 whether 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 two years before the CFDA-level funding shock, and (award ⩾ 2 years) indicates if the federal grant is received two 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 ⩾ 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.

publications. These results offer further confirmation of our identification approach.[34]

3. *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: (i) the total amount of federal funding in the field increases by at least 40% from the previous year; (ii) the increase in funding is temporary and the funding level reverts back to the preshock level at some later point in time; and (iii) there are no large positive or negative funding changes (> 30% or < –30%) in the two years preceding the shock. There are 27 positive shocks that satisfy these criteria. Online Appendix 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 positive shocks, but they have opposite signs and similar magnitudes as our baseline negative shocks in Table II. This indicates that the effects of changes to federal funding are at least weakly symmetrical for positive shocks.

4. *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 that has a large and temporary negative federal funding shock, researchers in that lab may leave, which could affect the lab's innovation outcomes at the extensive margin. To assess these possibilities, we define a lab as a team of researchers working under a common PI

34. One concern is that older grants may be correlated with lower quality of researchers. This is unlikely to drive the results for two reasons. First, most scientists work on grant cycles, and even the most productive ones do not get grants every year or every other year. Bigger grants also tend to last longer, which goes in the opposite direction. In fact, in the untreated group (which is not affected by the negative shocks), there is no significant difference in patents and publications between researchers with older grants and researchers with more recent grants. Second, if researchers with older grants are of lower quality, they should also have less patenting, fewer publications, and fewer high-tech startups, but instead they patent more.

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.[35]

The lab-level results are largely consistent with the main analysis. The results are reported in Online 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 in the lab on the intensive margin and changes due to the entry and exit of researchers on the extensive margin.

5. *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 Online 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 Online Appendix Table A.6, we cluster at the level of the researcher's main CFDA code, which is the CFDA code from which the researcher receives the most funding, to address correlation in the aggregate narrow field. The effects on individual funding (column (1)), high-tech entrepreneurship (column (2)), and patenting (columns (3) and (4)) are robust to both approaches. However, the effect on publications becomes insignificant. In unreported tests, the strong negative effects from Table V on high-impact journal, high-citation, and basic publications are robust to both alternative clustering approaches.

V. Mechanisms

In this section, we examine why cuts to aggregate federal funding affect the research outputs of individual researchers. Two

35. 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.

possibilities are that these cuts: (1) lower the level of a researcher's funding; or (2) alter the composition of a researcher's funding, that is, whether the funding is from the federal government, private firms, or other sources. We begin to assess these in Table VII. 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 Table II, column (1), suggesting that researchers substitute federal with nonfederal sources of funding after experiencing a negative shock to their federal funding.[36] We examine how the federal funding cuts affect researchers' funding from private firms. Table VII, column (2) 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%.[37] This suggests that researchers compensate for declines in federal funding by seeking more private funding.[38]

If such compositional changes away from federal and toward 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 IX, we plot the event studies for the shares of federal and private funding around the negative federal funding cuts. We see no pretrend and then a significant decline in the federal share over a three-year period after the cut, which subsequently levels out (Panel A). The inverse pattern appears for the private share (Panel B). Table VII presents the difference-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.

36. Online 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)).

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

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

TABLE VII

EFFECT OF FEDERAL FUNDING SHOCKS ON INDIVIDUALS' OVERALL FUNDING, PRIVATE FUNDING, AND SHARES OF FEDERAL AND PRIVATE FUNDING

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×year×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

Notes. The table reports changes in total funding, private funding, and the shares of federal and private funding relied on 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 III. The baseline sample is a person-year panel from 2001 through 2017 from 22 universities in the UMETRICS data. The dependent variables are the log of all funding (column (1)), the log of private funding (columns (2) and (3)), and the share of total funding amount, for a researcher in a given year, from the federal government (column (4)) and private companies (column (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 of 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

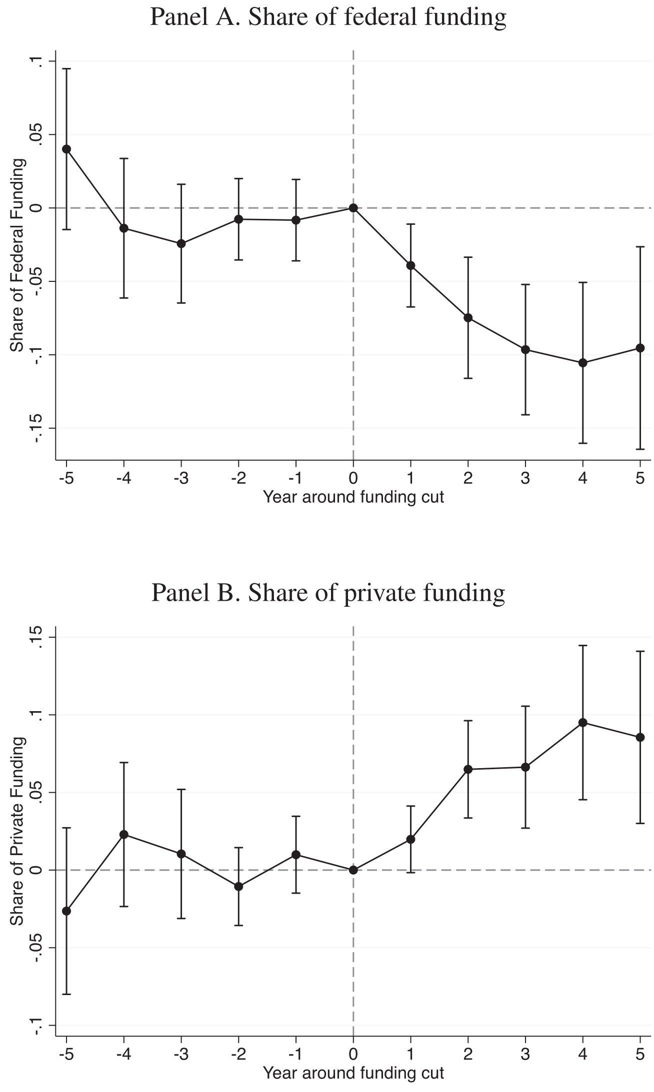

FIGURE IX

Shares of Federal and Private Funding Following Federal Funding Shocks

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.

In sum, the evidence supports the conclusion that changes to researchers' overall funding levels and the composition of funding play a role in explaining the effects of federal funding cuts on research outputs. We propose three nonmutually 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 fewer 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 VIII. 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.[39] Consistent with the productivity channel, federal grants tend to be larger monetarily and go to larger teams, and the subsequent research is cited more often and results in more 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 highly cited. Thus, at a purely descriptive level, it appears that all three channels may help determine research output.

39. In Table VIII, we do not include census outcomes due to constraints of 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 receive the majority of their funding from federal sources before the patent application date (or publication date).

TABLE VIII
SUMMARY STATISTICS BY FUNDING SOURCE

Funding type	Federal	Private	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	.000
Median total expenditure (thousands)	123.4	50.0	
Mean grant duration (years)	3.03	2.96	.000
Median grant duration (years)	3	3	
Mean team size	7.42	4.75	.000
Median team size	4	2	
Patent outcomes			
Number of patents	6,083	1,303	
Mean patent originality	0.274	0.291	.031
Mean patent generality	0.185	0.143	.000
Mean adjusted citation (by filing year and field)	1.19	0.895	.016
Percent of assignees that are private firms	3.3	5.7	.000
Publications outcomes			
Number of publications	448,714	61,293	
Mean journal impact factor	2.63	2.48	.000
Mean citation (with 3 years of publishing)	21.2	20.8	.183
Mean citation (all years)	42.4	39.8	.000
Mean appliedness score	0.102	0.184	.000
Mean citations by patents	0.125	0.127	.802

Notes. This table shows summary statistics for funding characteristics, research team sizes, and research outcomes for researchers funded by the U.S. federal government (column “Federal”) and by the private sector (e.g., corporations or nonprofits; 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 the 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.

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

1. *Research Productivity*

Since the aggregate negative funding shocks reduce researchers’ total funding and lab sizes, it is possible that our main results reflect a decline in research productivity due to the loss of resources coming from the overall decline in the level of a researcher’s funding. Research funding is crucial for acquiring inputs to the research process, including equipment, information technology, qualified personnel, and travel to conferences.

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 (1) more patents, (2) more high-tech entrepreneurship, and (3) 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.

2. Basic versus 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, in practice federally funded research is not necessarily more basic: the share of funding supporting basic research is essentially the same across federal and nonfederal funding sources (NSF 2018), partly because private funders often fund research in "Pasteur's quadrant," namely, basic research that is directed at real-world challenges or problems (Atkinson 2018).

If federal funding pushes researchers toward performing more basic research, we expect that more federal funding should yield fewer patents and less high-tech entrepreneurship for 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, and publications in more basic research. 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.[40] 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 cofounder, and Sadoway remained a full-time professor at MIT.[41] 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."[42]

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.

3. 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 toward 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 the training of future academics, and thus aims to fund innovation and research that is more widely accessible.[43] Hence, privately funded research might result in research outputs that are more often appropriated by the funder, while

40. 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 2022). This could have shifted all research in a more applied direction, regardless of funding source.

41. See https://ambri.com/company/ and Stauffer (2016).

42. See https://arpa-e.energy.gov/technologies/projects/electroville-grid-scale-batteries.

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

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

This hypothesis yields three predictions: (i) federal funding should yield fewer patents, which are important for appropriation by the private sector; (ii) federal funding should yield more high-tech entrepreneurship by university researchers (who are free to use the IP for the benefit of their companies); and (iii) 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 (i), 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 (ii) and (iii), the funding cuts have strong negative effects on high-tech entrepreneurship and publications. Because 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."[44] 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

44. See patent no. 6,286,999 B1 at https://patentimages.storage.googleapis.com/37/a9/18/d7c46ea42c4b05/US6285999.pdf and Hart (1994).

own research. This aligns with a common perception that firms sponsor academic research in part to train future employees.

In practice, the contracts between funders and universities support 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."[45] To explore this further, we reviewed 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 Online 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

45. See https://fingate.stanford.edu/purchasing-contracts/contracts.

officers, they emphasized that these tend to be a starting point for negotiations, with the firm typically imposing more stringent requirements.[46] Harvard University's standard contracts with industry, even before negotiations and for patents that Harvard has claimed for itself, states: "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 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—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 toward 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 note that multiple mechanisms could be at work to explain the effects we document.

VI. 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

46. These negotiations can be complicated. One scientist consulted by the authors recalled that a contact between the University of Massachusetts in Boston and Wayfair took a full year to negotiate.

intelligence, as well as companies such as Google and Genentech.[47] 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 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 and a change in composition away from federal and toward private funding. We propose three nonmutually 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). Although 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,

47. Google: NSF; see https://fingate.stanford.edu/purchasing-contracts/contracts. Genentech: NIH; see Cohen et al. (1973).

with many actively recruiting corporate research sponsors.[48] 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 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, Dewatripont, and Stein 2008). Our evidence supports this possibility.

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U.S. Census Bureau, United States
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Supplementary Material

An Online Appendix for this article can be found at *The Quarterly Journal of Economics* online.

Data Availability

Code replicating the tables and figures in this article can be found in Babina et al. (2022) in the Harvard Dataverse, https://doi.org/10.7910/DVN/EZZBCR.

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48. 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 https://www.mics.ece.vt.edu/.

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