The Color of Money: Federal vs. Industry Funding of University Research*

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Abstract

Universities are an important source of new knowledge. U.S. universities have traditionally relied on federal government funding, but since 2000 the federal share has declined while the private industry share has increased. This paper offers the first causal comparison of federal and private university research funding, focusing on patenting and researcher career outcomes. We begin with unique data on grants from 22 universities, which include individual-level payments for everyone employed on all grants for each university-year. We combine this with patent and Census data, including national IRS W-2 histories. We instrument for an individual's source of funding with government-wide R&D expenditure shocks within a narrow field of study. These funding supply changes yield a set of compliers who are pushed away from federal funding and into private funding. We find that a higher share of federal funding causes fewer but more general patents, much more high-tech entrepreneurship, a higher likelihood of remaining employed in academia, and a lower likelihood of joining an incumbent firm. Increasing the private share of funding has opposite effects for most outcomes. It appears that private funding leads to greater appropriation of intellectual property by incumbent firms.

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1 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 rates of corporate research funding for university research as one rationale (Markoff 2005). This example reflects a broader trend: The federal share of university research funding has declined steadily since the early 2000s, while the private share has increased (Figure 1; Mervis 2017). Despite the importance of university research to innovation and therefore to economic growth (Jaffe 1989, Audretsch and Feldman 1996), we know little about whether the returns to university research investment are sensitive to the source of funding. This paper helps to fill the gap.

On one hand, if the main motivation for government subsidy of science is underinvestment due to lack of appropriability by private firms, then the level of funding rather than the source may be most relevant (Nelson 1959, Arrow 1962). Indeed, the editor of the *New England Journal of Medicine* has argued that it is the quality of research, not its source of funding, that matters (Drazen 2016). There is evidence from the medical sciences that is consistent with this: Jacob and Lefgren (2011) find that researchers who lose grants shift to other sources of funding with little impact on their publications, Myers (2019) shows that researcher direction is not very sensitive to funding availability, and Azoulay et al. (2019) show how publicly funded research impacts private pharmaceutical innovation.

On the other hand, the decline in the federal share of university research investment has raised at least two concerns. First, federal funding has been perceived as an important source of transformational technologies.[1] For example, the internet and artificial intelligence, as well as companies such as Google and Genentech, all originated in federally-funded university research.[2] If private research tends to fund more applied work, there may be fewer opportunities for transformational innovations. Second, if corporate sponsorship leads more of the resulting intellectual

[1]For example, Rush Holt, CEO of the American Association for the Advancement of Science, wrote: "Private-sector spending is skewed more toward the development of products with marketable advantages than on longer-term research with applications that are not quite so clear, and so, corporate research, as beneficial as it may be, is no substitute for federal investment in research." https://www.nytimes.com/roomfordebate/2016/09/20/the-cost-of-corporate-funded-research/we-need-both-corporate-funding-and-federal-funding.

[2]Google: NSF; see https://patentimages.storage.googleapis.com/37/a9/18/d7c46ea42c4b05/US6285999.pdf. Genentech: NIH; see https://www.ncbi.nlm.nih.gov/pmc/articles/PMC427208/pdf/pnas00138-0206.pdf.

property to be privately appropriated, private funding may lead to fewer knowledge spillovers from university research.[3] Azoulay and Li (2020) argue that public sector grant funding has played an important role in ultimately important innovations, in part because the original research was conducted without conditions on its expected "usefulness." This suggests that facing unpredictable natural and man-made challenges, society benefits from investing in research in a wide variety of open-ended topics.

This paper makes three contributions. The first is methodological, providing a new instrument for the source of a researcher's funding. Our baseline data consists of information at the employee-year level about all employees paid by all grants at 22 U.S. research universities where we observe both public and private funds. For every individual researcher in each year, we observe all grants and expenditures, and we calculate the fraction of the researcher's expenditures that comes from the federal government, as well as the fraction of spending that is accounted for by private firms and other sources. The time frame for analysis, including all outcomes described below, is from 2001 to 2016. These data are available for academic use via the University of Michigan's Institute for Research on Innovation and Science, so our instrument can be readily deployed in future research.

The instrument addresses endogeneity in the relationship between funding source and research outcomes. For example, individuals who wish to do more applied work or have an interest in leaving academia may prefer industry funding, or higher quality researchers may select into federal grants. To eliminate these and other sources of bias, we use funding shocks within narrow government programs to instrument for the share of federal and private funding. Examples of the R&D programs, identified in a time-consistent manner by government codes, are "Nuclear Energy Research," "Cardiovascular Diseases Research," and "Healthy Marriage Promotion and Responsible Fatherhood Grants." Funding in these programs is governed by Congressional politics and is quite volatile year to year (see Section 2.2 for details). In robustness tests, we address potential concerns with the instrument, and show

[3] McCluskey (2017) writes, "Academics and university officials, for example, are constantly under increased pressure from corporate funders to agree to conduct studies that would remain the property of the funder...corporate backers can be given a great deal of power and latitude, selecting the specific kinds of studies, materials, and techniques to be used in exchange for their funding. Unsurprisingly, companies excel at creating the conditions most likely to give them the results they want."

that neither technological trends, downstream subsidies, nor predictability confound estimation. An advantage of our instrument is that it stems from actual policies — Congressional budget decisions – and thus the estimates from compliers are informative about the relevant policy counterfactual.

The second contribution demonstrates tradeoffs in patenting activity by funding source. We find that a higher share of federal funding makes a researcher less likely to patent on the extensive and intensive margins. For example, a 10% increase in the mean of the share of federal funding reduces the probability of any patenting by about 50% of the mean. Measures based on patent citations offer windows – albeit imperfect ones – into dimensions of knowledge spillovers. A higher share of federal funding increases the chances of producing a patent that is general, which means that it is more "basic" or general purpose (Trajtenberg et al. 1997). There is no effect on highly cited or original patents, despite the negative effect on patenting. In other words, when federal funding does lead to patents, they are more highly cited and more original on average, a fact that also appears in descriptive statistics. The share of federal funding also reduces the probability that patents have a private sector assignee. We find that a large fraction of patents with a private sector assignee are assigned to an industry funder of the research, consistent with privately-funded research more often being appropriated by the sponsor. When we split the sample by occupation, we find that faculty and, albeit to a lesser extent, graduate students explain the negative effects on patenting and the positive effect on having a general patent, consistent with them being the primary impetus of patent application decisions rather than undergraduates and staff, who comprise the other types of grant employees.

The third contribution of the paper focuses on human capital, assessing the effect of a researcher's funding source on her career outcomes. For this analysis, we link individuals employed on grants to data at the U.S. Census Bureau, including IRS W-2 tax records. Federal funding spurs high-tech entrepreneurship, with a 10% increase in the mean of the federal share increasing the probability of high-tech entrepreneurship by 56% of the mean. This points toward substantial knowledge spillovers, as high-tech new firms are an important source of economic growth and job creation, and university research is thought to be the origin of many high-tech startups (Feldman et al. 2002, Decker et al. 2014, Avnimelech and Feldman 2015). We also find that more federal funding decreases the probability that a researcher subsequently works for an incumbent firm and increases the probability of subsequently working at a university. Relative to the means, these effects are smaller in magnitude than the effect on high-tech entrepreneurship. The career effects vary by occupation. The large positive effect on high-tech entrepreneurship is driven by graduate students and, to a lesser extent, undergraduate students. Undergraduate, graduate students, and faculty all experience a negative effect of the federal share on working at an incumbent firm. Finally, undergraduate and graduate students explain the positive effect on working at a university.

While the independent effect of federal funding may be most policy-relevant, we are also interested in whether private funding yields opposite effects. It need not, as there are other funding sources, such as universities and state governments. When we deploy the same instrument but to predict the share of private funding, we generally find the reverse of the effects of the federal share, though some are larger in magnitude. For example, a 10% increase in the mean of the private share increases the chances of having a private assignee by 35% of the mean.

Three key robustness tests address potential concerns with the identification approach. First, it is possible that despite the field controls, technological opportunities or downstream subsidies explain both changes in federal R&D and changes in research outputs. To test whether this is occurring, we restrict the sample to researchers who do not switch between federal and private sources, as both of these drivers should also affect them. We find no effects among these non-switchers, consistent with a causal relationship between funding changes and different research outputs.

Second, we might worry that funding changes are predictable, and researchers adjust their career plans accordingly. In this case, the funding changes should exhibit long term incremental trends. (This is also the case for the technological opportunities story.) However, we find that controlling for long-term trends in funding does not affect the results, and we demonstrate no pre-trends in a visual event study. Third, there may be concern that loss of federal funding is a negative career shock even when the funding is replaced with private funding, and despite our controls for the individual's overall or change in expenditure. However, a higher federal share does not significantly increase wages, indicating that losing federal funds does not cause lower income. If a decline in the federal share represents a negative shock in other ways, such as prestige, which in turn changes the nature of work that an individual performs, this is not an identification problem but rather a potential mechanism for the causal effects.

Our results demonstrate that federal and private funding are not substitutes. They push university researchers in different directions, both in terms of intellectual property and the individual's career. Further, the story is more nuanced than one type of funding simply leading to more productive research. While federal funding yields fewer patents, it yields more startups. Federal and private research sponsorship could differ along three axes: (1) Productivity; (2) Basic vs. Applied; and (3) Open vs. Appropriated. In Section 5 of this paper, we discuss these in detail. While these – and perhaps other – channels may all be at play, our evidence is most consistent the third dimension, where private sponsors push researchers towards work that the firm can appropriate. This hypothesis stems from the common understanding that industry funders to have rights of first refusal to research findings, complex non-disclosure agreements, and some control over the direction of research (e.g. NAP 1993, McCluskey 2017).

First, the standard way to appropriate new ideas is to patent them, and we observe that private funding causes more patenting. We find that 40% of privately assigned patents in our data are assigned to the private sponsor. Federal research yields equally cited and more general patents, which are accessible to a broader range of future researchers. Second, private funding leads to much less high-tech entrepreneurship, consistent with federal funding having fewer strings attached, freeing intellectual property to be deployed by a startup. For example, Sergey Brin and Larry Page created the PageRank algorithm while PhD students at Stanford as part of their work for a grant from three federal agencies to develop a "Digital Library." They were able to make this algorithm the basis for their startup, 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. Third, we find evidence that human capital created by a private grant is also often appropriated by the funding firm, consistent with a common perception that firms sponsor research in part to train future employees. Among individuals with private funding who subsequently work at any funder firm (~500 firms), 20% go to the firm that funded their own research.

In sum, our findings indicate that a key difference between federal and private funding lies in contractual arrangements for how intellectual property is commercialized. This is important, given the evidence that more open science has greater spillovers (Williams 2013, Murray et al. 2016). Our evidence directly speaks to the longstanding tension between intellectual property rights and innovation; while patents may incentivize private firms to fund university research, these incentives go hand-in-hand with reduced spillovers (Scotchmer, 1991, Walsh et al., 2005, Azoulay and Li, 2020).

Our paper contributes primarily to two literatures. One studies the relationship between private and public funding, which has been subject to much debate. On one hand, Goolsbee (1998) argues that government efforts to increase inventive activity are problematic, because facing inelastic R&D worker labor supply, the government funding simply increases the wages of R&D workers. On the other hand, empirical evidence from the life sciences finds large positive impacts of public funding on private innovation (Azoulay et al. 2019). Budish, Roin and Williams (2015) document that private R&D investment in drugs is more sensitive than public investment to the time required for commercialization. Other work on the public funding of research includes Hegde (2009). There is some evidence from surveys, case studies, and university-level data that universities and public funding are associated with startup activity (O'shea et al. 2005, Åstebro et al. 2012, Zucker et al. 1998).[4] To our knowledge, we provide the first causal effect of the funding *source.*

We also contribute to the literature on how universities affect innovation, which beyond work cited above includes Shane and Stuart (2002), Lach and Schankerman (2008), Belenzon and Schankerman (2009), Foray and Lissoni 2010, Belenzon and Schankerman (2013), Guerzoni et al. (2017), Tartari and Stern (2018), Tabakovic and Wollmann (2019), and Watzinger and Schnitzer (2019). Especially related to and complementary with our findings, Azoulay, Graff Zivin and Manso (2011) show that rewarding long term success while tolerating short term failure leads to higher impact research, and Hvide and Jones (2018) show a negative effect on faculty entrepreneurship when invention rights were reallocated from the professor to the university.

[4] See Astebro and Bazzazian (2011), Djokovic and Souitaris (2008), Rothaermel et al. (2007), and Siegel et al. (2007) for review.

2 Methodology

In this section, we explain the university research setting (Section 2.1) and describe our empirical strategy (Section 2.2).

2.1 Background

A university researcher i can receive funding from multiple sources, including the federal government, private firms, local governments, and universities. The choice of funding source is not random and can depend on many factors. First, it depends on the type of research projects the researcher works on. Some research projects are more favored by the government, while others are more favored by private firms. Second, it depends on the researcher's preferences. For example, different types of funding may have different contractual arrangements and prestige, and different researchers may prefer different funding sources. Third, it also depends on the availability of funding from each source. For example, if federal funding is scarce and getting it is difficult, the researcher may opt for other types of funding instead even though she would prefer federal funding the most.

These factors can be grouped into two broad categories: demand-side factors and supply-side factors. Demand-side factors affect researchers' preferences for different funding sources, and supply-side factors affect the availability of funding from each source to the researcher and the research project being funded. Among the supply-side factors there are two sub-categories: one relates to the quality and type of the research being conducted and the quality of the researcher, and the other affects the availability of funding to everyone and does *not* depend on the identity of the researcher or the research project.

Regressing innovation outcomes on funding sources will reflect all of these factors. In particular, individual preferences and the quality ' and type of research projects are correlated with funding sources and with innovation outcomes. For instance, a researcher with a high-potential project is more likely to be funded by a highly selective federal grant from, say, the National Science Foundation (NSF), and this high-potential project is also more likely to generate patents ex-post. In this case the unobserved potential of the research project leads to a positive correlation between share of funding from federal government and patents. On the other hand, a project on rechargeable batteries with direct commercial applications may be more favored by industry funders than a research project on theoretical quantum physics, and is also more likely to lead to patents. In this case, the unobserved propensity for commercialization leads to a negative correlation between share of funding from federal government and patenting. Therefore, to identify the causal effect of funding sources on innovation outcomes, we need to isolate the exogenous components of funding sources that are uncorrelated with researchers' innovation outcomes.

2.2 Empirical Strategy

Our empirical strategy exploits the exogenous components of funding sources stemming from changes in aggregate supply of federal funding. We use changes in the amount of funding within narrow federal programs as a supply shock to the researchers receiving funding from specific programs. Since these funding shocks affect all researchers working in one area, they are uncorrelated with characteristics of individual researchers and research projects. The Catalog of Federal Domestic Assistance (CFDA), which is maintained by the government, identifies federal assistance programs.[5] Each CFDA program is related to a specific field of research. Two examples are shown in Figure 2: "Cardiovascular Diseases Research," or CFDA code 93.837, where we observe a positive shock in 2005, and "Agricultural Basic and Applied Research," or CFDA code 10.001, where we observe a negative shock in 2009. The intuition for the instrument is that if a researcher specializes in cardiovascular diseases, then when there is a drop in federal funding in this area, there will be less federal funding available to the researcher. As a result, the researcher will likely get a smaller fraction of her funding from federal government and a larger fraction from other sources, such as private firms.

To provide more insight into the sources of variation, consider two further examples. There is a CDFA program entitled "Healthy Marriage Promotion and Responsible Fatherhood Grants", (93.086).

[5] For more information, see https://www.rpi.edu/dept/finance/docs/tips/CFDA.pdf and https://www.govinfo.gov/app/details/CFR-2014-title2-vol1/CFR-2014-title2-vol1-sec200-10/summary.

Congress appropriated \$150 million for these grants for each year from 2006 to 2010 as part of the "Deficit Reduction Act of 2005," reflecting the Bush Administration's interest in marriage. These funds emerged from a complex political process linked to the reauthorization of the Temporary Assistance for Needy Families (TANF) program.[6] Reflecting a change in priorities, the amount was reduced to \$75 million per year under the Obama Administration, starting in 2011. A second example is the CFDA program "Basic, Applied and Advanced Scientific Research - Combating Weapons of Mass Destruction" (12.351). This began in 2007 with a budget of \$13 million and was described as the "first new basic research program in the Department of Defense in more than 30 years" aiming to "prevent hostile states and non-state actors from acquiring or using WMD."[7]

These examples highlight how the year-to-year changes in funding at the CFDA-code level typically reflect particular political priorities expressed through the Congressional budgeting process. Unlike countries such as China, the U.S. has no national innovation strategy, and there are no meaningful coordinated efforts across agencies or across time to invest in particular sectors or problems. The result is that funding in narrow fields of study often varies substantially year-to-year, and exhibits mean reversion. Importantly for our empirical strategy, the funding amount for each CFDA code is quite volatile year-to-year. Table 1 Panel A shows that the standard deviation of the log change in the amount of R&D is several times the mean. While our primary approach uses all changes, the results are robust to using only large shocks such as the ones cited for the examples in Figure 2.

One concern with using aggregate changes in funding within narrow fields is that universities or departments might respond differently to federal funding shocks to universities, and these responses might be correlated with research outputs. For example, some departments might be better than others at providing supplementary funding and attracting high-quality researchers. We address this concern by including university-department-time fixed effects. Identifying variation comes from comparing

[6] See The Congressional Research Services report "Welfare Reauthorization in the 109th Congress: An Overview" (January 23, 2007 (RL33418) https://www.everycrsreport.com/reports/RL33418.html)

[7] See Catalog of Federal Domestic Assistance, Volume 1, by Office of Management and Budget Office of Management and Budget, 2007, pg. 275; and Adams, Bianka J. and Harahan, Joseph P. Responding to War, Terrorism, and WMD Proliferation: History of DTRA, 1998-2008. DTRA History Series, Defense Threat Reduction Agency, (pg. 106).

colleagues working in the same department and in the same year, but on different topics that have different federal funding availability. Another concern is that the federal funding change could imply a negative economic shock to the researcher. To address the former concern, we control for the researcher's spending. We also show in Section 4.1 that, conditional on total funding, federal funding shocks do tend to shift researchers into private funding.

As we move toward formalizing the empirical strategy, it is useful to state the identifying assumption and potential threats at the outset. Validity of the instrument requires that among researchers in the same university department and conditional on the amount of funding, funding shocks in each researcher's respective federal programs affect outcomes only through the composition of funding sources. The threat to causal identification is from time-varying omitted variables that could contradict this assumption. These might relate to other supply-side factors, such as government subsidies for downstream technology deployment, or demand-side factors such as technological opportunities in the sector driving both researcher behavior and federal appropriations. We conduct robustness checks and placebo tests to address these concerns in the analysis below (Section 4.5).

The results of the robustness tests make any plausible source of omitted variable bias very unlikely, given that they would have to operate despite university-field-year fixed effects. That said, a downside of the IV strategy is that it is not as good as a true experiment, because government funding is not random. It is nonetheless a valuable step towards answering an important, novel question about innovation. The literature has found it challenging to find truly exogenous variation in studying innovation investment. For example, Kline et al. (2019) examine the effect of innovation on wages by comparing firms whose first patent application was granted with firms whose first patent application was rejected (with no examiner fixed effects), extrapolating the value of the patent from patents of publicly-traded firms. Bloom et al. (2013) instrument for innovation investment using state and federal tax credits. While such strategies also lack truly experimental variation, they represent the frontier of empirical research on innovation. Further, an advantage of our instrument is that it stems from Congressional budget decisions, making the estimates informative of the counterfactual effect of government funding changes. That is, the marginal effect we identify among compliers is what we are interested in to evaluate the policy change most relevant to our research question.

We now formally describe the instrument construction and empirical strategy. Suppose researcher i gets a fraction s_{it} of her total funding in year t from the federal government, and $(1 - s_{it})$ from other sources. The instrument for s_{it} consists of lagged changes to funding in programs from which i has previously had grants. Specifically, we use Equation 1 to measure aggregate changes in availability of federal funding to a researcher using the weighted average of changes in federal funding across all CFDA programs funding the researcher:

$$FS_{it} = \sum_j \frac{A_{ij}}{\sum_j A_{ij}} \log(\frac{F_{j,t}}{F_{j,t-1}}). \tag{1}$$

In this expression, A_{ij} is the amount of funding researcher i receives from CFDA program j, and $A_{ij}/(\sum_j A_{ij})$ is the share of researcher i's federal funding that is from program j. $F_{j,t}$ is the total amount of funding in program j in year t. The term is a researcher-level weighted average of log changes in the amount of funding from federal programs. It is important that the variation in this measure across researchers is unrelated with individual preferences or type of research, and comes entirely from the variation in the field of specialization, which is pre-determined.

We use the following IV model:

$$y_{iudt} = \beta_1 \hat{s}_{i,t-1} + X'_{i,t-1}\beta_2 + \delta_{udt} + \varepsilon_{it}. \tag{2}$$

where y_{iudt} is the innovation output (patents, startups, or publications) or career outcomes of researcher i in field d from university u in year t. $\hat{s}_{i,t-1}$ is the share of funding from federal government in year $t-1$ instrumented with lagged changes in aggregate federal funding $FS_{i,t-2}$ and $FS_{i,t-3}$.[8] We include a one-year lag to take into account the time lag between the innovation process and observed innovation output. $X_{i,t-1}$ include lagged amount of funding the researcher receives. We also include university-field-year fixed effects δ_{udt} to control for time-varying shocks to research productivity at university

[8]This is because there are usually some lags between changes of funding availability and switching of funding sources.

department level. The results are robust to using shorter and longer lags, and to using the level of funding with CFDA fixed effects rather than changes.

Our instrumental strategy is similar to the Bartik-style shift-share instrument, since we use aggregate changes in supply of federal funding relative to other types of funding to instrument for the share of federal funding at the individual level, with the weights given by individual exposure to federal CFDA programs (Goldsmith-Pinkham et al. (2019); Autor et al. (2013)). The identifying assumption is that the CFDA program shares are uncorrelated with the time-varying errors of innovation outcomes conditional on our controls. According to Goldsmith-Pinkham et al. (2019), one way to test the plausibility of the assumption is to check whether there are pre-trends before the shocks. We test for pre-trends in 4.5 and find that future shocks in federal funding do not predict past changes in innovation outcomes.

3 Data

This section discusses the data sources and how they are combined to create our estimation sample. Our analysis is based on human resource records from universities (Section 3.1). We first merge the data with expenditures in federal assistance programs from Single Audit (Section 3.2). We then link the university researchers to inventors to get patenting outcomes (Section 3.3). Finally, we obtain career outcomes from confidential administrative data at the U.S. Census Bureau (Section 3.4).

3.1 UMETRICS Data

We use new grant administration accounting records from the IRIS UMETRICS program to measure funding of university researchers. Universities contribute grant-level accounting data to this program, which is administered by the Institute for Research on Innovation and Science (IRIS) at the University of Michigan. Currently, 49 universities, accounting for more than 40% of federal R&D expenditures, are committed to participating, but the project is expected to become a national program.

For each grant, we observe both the name of the external funding source as well as the CFDA code for federal agency sponsors. There is only one CFDA code per grant. We use a combination of the CFDA codes and the names of external funders to determine if a grant came from a federal government agency, private firm, state or local government, foreign government, or university.[9] For every individual researcher in each year, we observe all of the research grants the researcher receives and her expenditures for each grant. We calculate the fraction of the researcher's expenditures that comes from the federal government, as well as the fraction of spending that is accounted for by private firms and other sources. For each researcher we also have a unique employee number, which allows us to track individuals over time. In addition, we observe each researcher's occupation classification (e.g. faculty, graduate student or post-doc, undergraduate student, and other) and department (e.g. physics, biology, etc). For simplicity of exposition, we refer to graduate students and post-docs as simply "graduate students." While the coverage of federal grants is complete, the coverage of non-federal grants is incomplete at some universities. Since our instrument only applies to people who have ever got funding from federal government, we exclude from our sample universities that do not supply information on funding from non-federal sources.

The final sample consists of 22 universities and around 235,000 researchers from 2001 to 2016. Table 1 Panel A presents summary statistics on the sample used in estimation. Among the researchers, 19% are faculty, 29% are graduate students, 38% are staff members, and 13% are undergraduate students.[10] More than 20% of the researchers have received funding from both federal government agencies and private companies. On average researchers receive funding from two federal assistance programs from the CFDA list.

3.2 Spending Shock Instruments

We measure federal funding shocks at CFDA-program level using Single Audits. All non-federal entities that spend $500,000 or more of federal awards in a year ($300,000 for fiscal years ending on

[9] We also use funder names to categorize industry funders into for-profit firms and nonprofit organizations, although in many cases it is ambiguous whether the company is for-profit or nonprofit from the names. Nonprofits not explicitly categorized as such are included in the private category.

[10] Staff includes Clinician, Staff Scientist, Research Analyst, Technician, Research Support, Technical Support, Research Administration, Research Coordinator, Instructional, and Other Staff.

or before December 30, 2003) are required to obtain an annual audit in accordance with the Single Audit Act Amendments of 1996. A Single Audit encompasses an examination of a recipient's financial records, financial statements, federal award transactions and expenditures, the general management of its operations, internal control systems, and federal assistance it received during the year.

We collect our data from the Federal Audit Clearinghouse, to which the Single Audits are submitted. The data contains both R&D and non-R&D expenditures by CFDA program by recipient by year. We aggregate R&D expenditures by CFDA programs across all recipients to measure the total expenditure of each CFDA program in a given year. Our instrument is the weighted average of changes in log expenditures across a researcher's CFDA programs (see Equation 1). Total expenditures within CFDA programs fluctuate dramatically – the standard deviation of our instrument is approximately 1.1, compared to means of 0.06 and 0.09 for the first two lags (see Table 1). Two characteristic examples (discussed above) are in Figure 2.

3.3 Patent Data

Patent data is from the PatentsView database, which contains bibliographic information on all patents granted by the United States Patent and Trademark Office (USPTO). Established in 2012, PatentsView longitudinally links inventors, assignees, locations and patenting activity using bulk data from the USPTO on published patent applications (2001-present) and granted patents (1976-present). Data on patent inventors from PatentsView were linked to UMETRICS employees by comparing names, affiliations, and grant numbers and constructing a similarity measure based on the textual similarity of the last names, middle initials, and first names. In addition, our matching algorithm examined the university affiliation of the employee with the assignee name listed on the patent and the geographic location listed for the inventor. After comparing names and affiliations, the decision of whether or not a pair matches was based on empirical probabilities from a training dataset of known matches.

In addition to the number of granted patents, we construct several variables to measure characteristics of patents that are standard in the literature. The first is the number of forward citations, which we normalize by patent class and by year to adjust for the systematic differences across classes and years. The citations data, from Babina et al. (2019), are updated as of the end of 2019. Forward citations are informative about the impact of a patent on future research. The second measure is generality. A high generality score indicates that the patent influenced subsequent innovations in a variety of fields and is more "basic" (Trajtenberg et al. 1997). Generality for patent i is defined as $1 - \sum_j s_{ij}^2$, where s_{ij} is the percentage of citations received by patent i that belong to patent class j. Thus, if a patent is cited by subsequent patents that belong to a wide range of fields the measure will be high, whereas if most citations are concentrated in a few fields it will be low (close to zero). The third measure is originality. The originality score will be low if a patent cites previous patents in a narrow set of technologies, whereas citing patents in a wide range of fields leads to a high score. Originality for patent i is defined as $1 - \sum_j c_{ij}^2$, where c_{ij} is the percentage of citations that patent i makes that belong to patent class j. The last measure is whether the assignee is a private company. We use the name of the assignees to identify whether a patent is assigned to a private company or other entities (e.g. universities).

Panel B of Table 1 presents the summary statistics for patents. About half of the patents receive zero citations. We define a patent as *highly cited* if its standardized citation count is in the top 10% of the (standardized) citation distribution. We define a patent as *original* or *general* if the originality or generality score is above the median in a given year.[11] About 1% of researchers have been granted a patent, and around 4% of all granted patents are assigned to private companies.

3.4 Entrepreneurship and Employment

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

We construct career outcomes for each UMETRICS individual by first linking them to

[11] These are based on within-year comparisons, because the generality and originality measures tend to be positively correlated with the number of citations made (for originality) or received (for generality) and therefore correlated with the year of the patent.

employment and wage information contained in W-2 tax records and the LEHD Person History File (PHF).[12] The LEHD PHF is derived from state unemployment insurance (UI) records and contains quarterly information on wages for nearly the universe of individuals in participating states as well as from the federal government (McKinney and Vilhuber, 2011).[13] The W-2 records include annual wages with complete coverage for all states from 2005 to 2017. They are reported to the IRS by individuals' employers and are required for any employee with tax withholdings or for whom taxes would have been withheld if not for an exemption claim. This includes industries and workers who are not covered by unemployment insurance. Crucially for our setting, the W-2 records include graduate student stipends. By linking UMETRICS individuals to these administrative data sources, we are able, with a high degree of confidence, to track each person's full domestic job history.

Both of these administrative data sets, the W-2 records and the LEHD PHF, include identifiers for the entities from which individuals receive their wages, allowing us to link firm-level information to each record. Characteristics of employers include age, industry, annual number of employees, annual payroll, and whether the employer is a university.[14] This information is sourced from the BR/LBD, the LEHD Employer Characteristics File (ECF), and the Integrated Postsecondary Education Data System (IPEDS). The BR is the Census Bureau's comprehensive list of all business establishments in the United States and contains information on each establishment's employment, payroll, industry (NAICS code), EIN, and a firm identifier developed by the Census Bureau (DeSalvo et al., 2016).[15] The LBD links establishments in the BR over time, which allows us to obtain the age of each firm (Jarmin and Miranda, 2002). The LEHD ECF is the universe of establishments that report earnings to state

[12]All person level Census data is identified by Protected Identification Keys (PIKs), confidential person identifiers at the U.S. Census Bureau that map, one-to-one, to Social Security numbers and allow for person- level linkages across a wide variety of Census Data. The information provide by university human resources in UMETRICS, provided by IRIS, is used to assign each UMETRICS employee ID a PIK.

[13]Certain job categories are excluded, such as agricultural workers, railroad employees (employees whose work crossed state-lines did not nearly fit into state administer programs, these issues were later resolved, but the carve out remains) and graduate students receiving a stipend. Each state must choose to participate in the LEHD programs, so years included are different for each state (and DC).

[14]The Census's current tracking of firms only goes back to 1976, so any firm founded before 1976 is simply "left censored" in age.

[15]Some industries are not as well tracked as others, these tend to be crop and animal production; rail transportation; National Postal Service; pension, health, welfare, and vacation funds; trusts, estates, and agency accounts; public administration, and establishments reporting government employees (e.g. state universities).

unemployment insurance agencies, and contains information on employment, payroll, industry, and the Census-developed firm identifier (McKinney and Vilhuber, 2011). IPEDS is a database maintained by the National Center for Education Statistics (NCES), and provides a wide variety of information on colleges, universities, and technical and vocational schools in the United States. Crucial for our analysis, IPEDS provides the EIN for a comprehensive list of universities, allowing us to identify earnings that UMETRICS individuals receive from universities.

As noted the LEHD ECF includes information on industry (NAICS codes) that is provided by the states as part of UI programs. In addition, the LEHD staff has used information from the LBD to attach firm identifiers and firm age to firms in the ECF.[16] To attach these firm characteristics the W-2 records, we merge information from the ECF using the EIN (within year, and then within two years on either side of the target year). When an EIN-year in the W-2 records is not in the ECF, we use the BR to obtain information on the firm identifier and the model NAICS by BR employment and use the LBD to obtain information on firm age and size.[17] High-tech NAICS are defined according to the NSF classification.[18] These datasets are combined to create a complete job history panel. We define all outcome variables on the LEHD sample and W-2 sample separately. In a second step, for each PIK-year we take the maximum of the two values. For instance, we create a dummy variable if a person receives wages from a high-tech startup in a year from the LEHD data and the W-2 data separately, then if for a PIK-year this variable takes on a value of one in *either dataset*, the final value for the PIK-year is one. Incorporating information from the W-2 records increases the number of observed PIK-years by about 20%.

Using this full panel of linked data, we construct the following key outcome variables, which characterize the entrepreneurial and employment activity of each person-year: 1) an indicator for whether the individual works at an age-zero high-tech firm this year or in the next two years (*high-tech entrepreneurship*), 2) an indicator for whether the individual works at an age-five or older

[16]Different industries pay different UI rates, thus industry tracking is important to the UI programs.

[17]To find the correct firm in the BR, a window of years is used for this process as well, target year, target year plus one, target year minus one, target year plus two, and finally target year minus two. To find the NAICS, first we look for the largest employment by two-digit industry code and then, within this industry code, we take the largest employment three digit code. We continue this process until a full six-digit NAICS is identified.

[18]See https://www.nsf.gov/statistics/seind14/index.cfm/chapter-8/tt08-a.htm.

firm this year or in the next two years (*incumbent employment*), and 3) an indicator for whether the individual works at a university this year or in the next two years (*university employment*).[19]

We define several additional career outcome variables: 4) an indicator for whether the individual works at a firm aged zero this year or in the next two years (*entrepreneurship*), 5) an indicator for whether the individual works at a firm aged five years or fewer this year or in the next two years (*employment at young firm*), 6) an indicator for whether the individual works at a high-tech firm aged five years or fewer this year or in the next two years (*employment at young high-tech firm*), 7) an indicator for whether the individual works at a high-tech firm that is at least five years old this year or in the next two years (*employment at incumbent high-tech firm*), and 8) log wages, in real 2014 dollars. We define an individual's wage using their dominant job—that is the job from which they are paid the most.

4 Results

4.1 First Stage

We begin by reporting the first stage results in Table 2. We show two lags of the log change in government-wide R&D expenditure in individual i's CFDA code (federal program area, often corresponding to a narrow field of study). For example, Log-change Amount R&D$_{i,t-1}$ is the logged difference between year $t-2$ and $t-1$ in R&D expenditure for i's CFDA. The dependent variables are the share of an individual's funding that is from federal government sources (column 1), private sources (column 2), and other sources such as the university, known non-profit organizations, or state government (column 3). Both lags are significant at the .01 level. As an example of interpretation, the coefficient on Log-change Amount R&D$_{i,t-2}$ implies that a one standard deviation increase in this variable increases the share federal by 0.5%. The relevant statistics for this and subsequent calculations are in Table 1.

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

The instrument also negatively affects share of funding from industry funders and other sources. A one-standard-deviation increase in R&$D_{i,t-2}$ is associated with an reduction in share of funding from private companies by 0.32% and a reduction in share of funding from other sources by 0.11%. In general the effects of federal funding shocks are much bigger for share private than share other. This suggests that fluctuations in the share of federal funding due to funding supply shocks is mostly compensated for by a shift in the share for private industry funding, as Figure 1 shows.

These instruments are very strong. For the share of funding from federal sources, the Cragg-Donald F-statistic, at 117, is above the rule-of-thumb threshold of 10 defining a weak instrument. The results in both the first and second stages are very similar when we use only the first lag (Log-change Amount R&$D_{i,t-1}$) or five lags. Also, the results are robust to an alternative approach of using the log amount of expenditure rather than changes and adding CFDA fixed effects. Expenditure positively predicts the shares of funding from federal and private sources, and negatively predicts the share of other types of funding. This is intuitive, since federal and private grants are typically larger than grants from universities and other local sources of funds.

4.2 Patent Activity

The main results of the paper documenting the effect of the instrumented share of federal funding on innovation and career outcomes are contained in Tables 3-7. We begin with patent activity in Table 3. Note that all regressions in this table include controls for the individual's total expenditure (which, intuitively, positively predicts patent activity) as well as university by year by field fixed effects. For all the results, the F-statistic on the first stage regression is shown at the bottom of the table.

Granted patents serve as a proxy for innovation with commercial application. That is, we expect that if researchers intend to have a practical private sector use for their outputs, then more productive research will be associated with more patents. However, patents also reflect a decision to engage in the requisite disclosure and costs associated with applying for a patent, implying intent to create contractible intellectual property; alternatives are to publish the invention as openly available science, or maintain it as a trade secret. We find that a higher share of funding from federal sources leads to a lower chance of having any patents and fewer patents (columns 1-2 of Table 3). Specifically, the interpretation of the coefficient in column 1 is that a 10% increase in the mean of the share of federal funding reduces the probability of any patenting by 0.4 percentage points. This is about half the mean, which is 0.9%. We find a similar result on the intensive margin, where a 10% increase in the mean of the share of federal funding leads to .006 fewer patents, which is 56% of the mean. While there is also a negative effect on the number of patents conditional on patenting, this result is largely a byproduct of the extensive margin effect.

Patents vary widely in their quality and importance to future research. We are interested in two measures that are informative about how useful the patent is for future research, providing a window into potential knowledge spillovers. The first is citations, which proxies for how intensively a patent is related to or is the basis of future inventions. Surprisingly in light of the large negative effect on patents, there is no relationship between the federal share and the probability of having any highly cited patents (column 3). We do find a negative effect of the federal share on patent originality, which measures the breadth of inputs into a given patent (column 4). A 10% increase in the mean of the share of federal funding reduces the probability of an original patent by about 35% of the mean.

The second measure of a patent's usefulness for future research is generality. We find that the share of funding is associated with a higher probability of having a general patent in column 5. A general patent is cited by patents in a broader range of classes, indicating that the invention is more basic and general purpose. The positive effect is quite striking given that it must overcome the lower average probability of any patenting. The coefficient means that a 10% increase in the mean of the federal share increases the probability of having a general patent by 55% of the mean.

The last result in the table, in column 6, shows that the share of federal funding reduces the probability that patents have a private sector assignee. 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 the funder licensing the patent, in which case there is often a reassignment. This result points towards federally-funded patents being less immediately appropriated by the private sector.

The above results suggest that when federal funding does lead to patents, they are actually more highly cited on average. The raw means are consistent with this conclusion. Table 4 compares patents from grants with federal, private, and other sources of funding. The average citations for federal patents is 0.82, compared to just 0.35 for private patents. The average share of patents that are original is 32% for federal funding, and 27% for private funding. The table also shows that private funding yields a higher percentage of assignees that are private firms. All of these are significantly different from one another at the .01 level except for originality. It is important to note that the raw means reflect selection rather than causal effects. However, as we discuss below, the OLS results for patenting are largely similar to the IV results. Therefore, it is reasonable to treat these summary statistics as informative about the mechanisms at play in both OLS and IV.

To confirm our empirical strategy and describe the timing dynamics, we conduct an event study using large funding shocks. This exercise serves three purposes. First, it demonstrates an absence of pre-trends. Second, it offers compelling evidence of the dynamics (i.e. timing) of our effects. Third, it offers evidence against the hypothesis that technological opportunities are an omitted variable driving both funding changes and research outputs, because such opportunities should manifest themselves in secular changes to both funding and outcomes, leading to null or attenuated effects from one-time shocks (this hypothesis is discussed and tested further in Section 4.6).

Using only large, temporary funding shocks, we estimate the following regression:[20]

$$y_{iudt} = \sum_{\tau=-5}^{5} \beta_\tau D_{i\tau} + X'_{i,t-1}\gamma + \delta_{udt} + \epsilon_{it}.$$

Here, the vector $D_{i\tau}$ is composed of a separate indicator variable for each of the years before and after the funding shock. τ is normalized so that it is equal to zero in the year with the funding shock; it ranges from -5 (for 5 years before the funding shock) to 5 (5 years after the shock). All τs are set equal to zero for researchers whose CFDA codes did not experience a negative shock. The regression

[20] We define large, temporary funding shocks as cases that meet the following conditions: (1) the total expenditure of federal funding drops by at least 40% from the previous year; (2) the decline in funding is temporary and the funding level reverts back to the pre-shock level at some later point in time; (3) there is no big positive or negative funding changes (>20% or <-20%) in the two years preceding the shock. The 20th percentile of funding changes is -40%. Results are similar when using slightly higher (-30%) or lower (-50%) cutoffs.

controls for university-year-field fixed effects and lagged funding expenditure.

The results are as follows. First, Figure **??** shows that these large negative shocks to the researchers' funding predict that the share of federal funding declines and the share of private funding increases following the shock. Importantly, there are no differences in the evolution of share federal and share private before the shock. This suggests that large shocks to federal funding pushes university researchers away from federal to private funding.

Second, in Figure 4, we examine the evolution of patenting around these large shocks to researcher federal funding, and find that patenting declines following the shock, measured with either the probability of patenting (in the top graph) or the number of patents (in the bottom graph). This results provides additional evidence that the shocks to federal funding leads to a larger reliance on private funding, and lower patenting rates by those who are affected by the shock.

To understand the channels explaining our effects, we estimate our main model separately for researchers at different stages of their careers. We employ all of the occupation classes that we observe: faculty, graduate students, undergraduate students, and staff. Consistent with faculty and graduate students being the primary impetus of patent application decisions, Table 5 shows that the negative effects on any patents and number of patents are driven by these two groups. As might be expected, faculty are much more likely to have multiple patents, so they are responsible for the negative effect on the intensive margin (column 2). Graduate students appear more responsible for the extensive margin effect (column 3). The coefficients are small and insignificant for undergraduates and staff, which is intuitive. The result (not reported) is similar for general patents, with faculty and graduate students driving the effect.

4.3 Career Outcomes

The second dimension of research output that we consider is the individual researcher's career trajectory. All of the outcomes are measured in the three years following the year that funding source is observed. Otherwise, the model is the same as in Table 3. We are especially interested in high-tech entrepreneurship given its important spillover benefits and perceived ties to university research. Table

6 column 1 shows that the share of federal funding has a very large positive effect on high-tech entrepreneurship. The coefficient of 0.0509, significant at the 0.01 level, means that a 10% increase in the mean of the federal share increases the probability of high-tech entrepreneurship by 56% of the mean.[21]

We also find that an increased federal funding share significantly decreases the probability that a researcher leaves academia to work for an incumbent firm, defined as a firm that is more than five years old (column 2), and significantly increases the probability that she works for a university (column 3). Note that these career outcome variables are not mutually exclusive, because individuals have a variety of other possible outcomes: they can leave the country, leave the U.S. labor force, work at a non-profit or for government, or join a firm less than five years old. Also note that the means add up to more than one because individuals can work for both industry and academia in the three years following the period their research funding is observed. Relative to the means, these effects are smaller in magnitude than the effect on high-tech entrepreneurship. A 10% increase in the mean of the federal share decreases (increases) the probability of working for an incumbent firm (university) by 14% (5%) of the mean.

In Appendix Table A.1, we examine how additional career outcomes vary with the instrumented researchers' federal funding share. In column 1, we find that, in contrast to high-tech entrepreneurship results, the instrumented federal share of funding predicts lower probability of departing to entrepreneurship in general, which overwhelmingly consists of low-tech and low-growth entrepreneurship (note the mean of this variable is 3%, relative to 0.74% for high-tech entrepreneurship). We find similar negative results when we examine the departures to young firms, defined as firms no more than five years old (column 2). However, when we limit the departures to high-tech young firms, we find that a 10% increase in the mean of the federal share of funding predicts a 29% from the mean rate of departures to young high-tech firms, which is equal to 2.2% (column 3). In contrast, column 4 shows no significant on the departures to high-tech incumbents, which are firms older than five years of age. The final column 5 shows that a higher federal share of funding does not a significantly affect wage in year t.

[21]The mean is 0.74%. The calculation is 56% = 0.0509*(10%*0.816)/0.0074, where 0.816 is the mean of federal share.

In sum, a higher federal share of researchers' funding increases the probability of staying at a university or launching a high-tech startup, and decreases or has no effect on the probability of all other outcomes that we have considered.

We next examine how the federal share's causal effect on career outcomes varies by researcher occupation in Table 7. The large positive effect on high-tech entrepreneurship is driven by graduate and undergraduate students (columns 1 and 4 of Panel A), with faculty and staff having an insignificant and economically small effects (columns 1 and 4 of Panel B). Note that the sample of graduates students is much larger than the sample of undergraduates, which may help explain the insignificant, albeit large, effect among undergraduates. The negative effect on working at an incumbent firm is driven by undergraduates, graduate students, and faculty; there is no effect among staff. The positive effect on working at a university is driven by undergraduates and graduate students, while the federal share of funding has no effect on working at university for faculty and staff. Even with the smaller samples, the F-statistics for all of these results are well above the rule of thumb cutoff of 10.

These results are intuitive. The source of funding has its most profound impacts for student researchers, who are at a crucial juncture in their career paths, deciding whether to stay in academia, help found a high-tech startup, or work at an incumbent firm. Through its effect on students, a higher share of federal funding stimulates high-tech entrepreneurship, which is important for economic growth and long-term innovation. Among faculty, the only significant effect is on their chances of joining an incumbent firm. This indicates that a lower share of federal funding makes leaving academia more appealing for professors. In many hard science fields, losing high-quality faculty to the private sector, which can typically pay more, has been identified as an important concern (Gofman and Jin (2020)). For example, one popular press article asked, "If industry keeps hiring the cutting-edge scholars, who will train the next generation of innovators in artificial intelligence?"[22] The absence of effects among staff (e.g., lab technicians) is to be expected, as these individuals are typically more set in their career paths and are generally less involved in the creative aspect of

[22]See https://www.bloomberg.com/opinion/articles/2019-01-07/tech-giants-gorging-on-ai-professors-is-bad-for-you and https://www.nytimes.com/2019/09/06/technology/when-the-ai-professor-leaves-students-suffer-study-says.html.

research.

4.4 Share of Private Funding

The results thus far have focused on the share of funding from federal relative to all other sources. The independent effect of federal funding is most relevant to policy, but we are also interested in whether there is a tradeoff with private sources of funding. As there are clear incentive differences between industry and government funders, this will shed light on the relationship between incentives and university innovation, with the instrument permitting the estimated effects to be independent of the particular researcher, conditional on the researcher being a complier. In Tables 8 and 9, we repeat the analysis from Tables 3 and 6 but with the instrumented share of private funding as the independent variable of interest. Recall that the shares of federal and private funding do not add to one, because there are a variety of other funding sources, such as universities and state governments.

Table 8 shows a strong positive effect of the private share on the probability of having any patents (column 1) and the number of patents (column 2). The effect in column 1 indicates that a 10% increase in the mean of the private share increases the probability of patenting by 9% of the mean. Despite leading to more patents, an increase the share of private funding does not increase the probability of having a highly cited patent (column 3). The subsequent columns contain results that are the inverse of the federal share findings, but somewhat larger in magnitude. Column 5 shows that a higher share of private funding reduces the probability of having any general patents (again, this is quite striking given its large positive effect on the probability of any patent). Last, column 6 shows that the private share dramatically increases the probability that a patent has a private assignee. The coefficient implies that a 10% increase in the mean of the private share increases the chances of having a private assignee by 35% of the mean.

The effects of the instrumented private share on career outcomes are in Table 9. An increase private share reduces the chances of becoming a high-tech entrepreneur, increases the chances of going to work for incumbent firms, and decreases the chances of working for the university. Hence, the results are inverted when we consider private funding, compared to federal funding. This inversion suggests that the shocks to federal funding are not compensated by increases in other funding sources, such as the university or local government funding. Moreover, the results that the share of private funding positively affects the departures to incumbent firms (that by construction provide private funding) is quite intuitive, since one potential goal for firms to fund university research is to invest in the development of skills that are useful to the firms. While examining a causal effect of the firm-sponsored funding of university research on the firm's hiring of the funded researchers is beyond the scope of this paper, we provide an intuitive statistic that point to this connection: we find that among people who have private funding and later go work for one of the funding firms 20% work at the firm that funded their research.

4.5 Robustness Tests

In this section, we describe robustness tests that address the primary potential concerns with the main analysis. \

4.5.1 Level of Funding

An important aspect of our analysis the focus on the source of funding rather than the level of funding. We therefore instrument for the source while controlling for the level. However, this raises the concern that level is also an endogenous variable. This could introduce bias to the degree a "bad control" has been included. There is also the possibility that our main effects in fact reflect the denominator of federal share. For example, the shock to federal funding could lead to a decrease in total funding, which would no doubt affect research outputs. That is, rather than the share of federal funding explaining the results, expenditures or change in expenditures drives the results so far, but rather its denominator—the total expenditures, which we control for in all regressions.

In contrast to this hypothesis, our focus on share stems from from the fact that total researcher expenditure and change in expenditure have either quite different or no effects on our outcomes of interest. We show this Table 10, where we use the same specification as in the main tables, but instead of instrumenting for the federal share, we instrument for the total lagged log expenditure to examine its effect on the key patent variables (columns 1 and 2) and career outcomes (columns 3–5). The instrument remains very strong. There is no causal effect of the level of expenditure on having any patents, and just a small negative effect on number of patents that is more than an order of magnitude smaller than the main effect from Table 3. There is no effect on high-tech entrepreneurship (column 3), and the effects on working at an incumbent firm or for a university are economically small, at 1.7% and 0.5% respectively using our standard interpretation, and are also the opposite signs as the main results.

We also show that the results are robust to alternative expenditure controls in Appendix Tables A.6 (patents) and A.5 (career outcomes). For each outcome, we show three models. The first includes the log change in expenditure between year $t-2$ and $t-1$. The second includes two lags of expenditure rather than one. The third omits the expenditure control entirely. The results are generally insensitive to these additions, with the exception of extensive margin patenting, which becomes just barely insignificant. All the career results, and our key patenting results for number of patents, patent generality, and private assignees remain robust.

These results, together with the absence of an effect on wages in Appendix Table A.1, indicate that the decline in federal share does not serve as a negative career shock through lower expenditure. Importantly, if a decline in the federal share represents a negative shock in other ways, such as prestige, which in turn changes the nature of work that an individual performs, this is not an identification problem but rather a potential mechanism for the causal effects.

4.5.2 Standard Errors

First, it is possible that researchers in the same university and field might experience correlated shocks to federal funding, making it inappropriate to cluster standard errors at the individual level. In Appendix Table A.4, we report the main results with clusters at the university-by-field level. The results for patenting and the key career outcomes remain robust, though the effect on generality becomes slightly more imprecise and (barely) loses statistical significance. The results are robust to other cluster assumptions, such as by CFDA code.

4.5.3 Alternative Channels

There may be concern that there are omitted variables correlated with both changes to government funding and research outputs. There are two plausible channels: technological opportunities in the sector that drive both federal funding changes and researcher decisions, and downstream federal incentives that pull researcher funding and are determined alongside upstream federal research investment. For example, if the government has an overall interest in solar energy, they may both fund research and offer deployment subsidies, leading to higher rates of patenting. While the negative effect of federal share on moves to incumbent firms might seem to push against the downstream subsidy story, government subsidies may be especially valuable for constrained new firms, and therefore encourage more startup entry but not be as relevant to decisions to move to incumbent firms.

A single exercise tests whether either of these channels are at play. Both the technological opportunities and downstream policies stories predict that researchers in the same CFDA code but who are not compliers with the instrument should also respond to the funding changes. In Appendix Table A.7 columns 1–2 we restrict the sample to individuals who do not alter the balance of federal and private funding sources during the sample period ("non-switchers"). We examine whether changes in federal R&D in their CFDA code have any predictive power over their patenting activity. This placebo test finds a near zero, insignificant result. This means that for these alternative mechanisms to explain our results, there must be something different about researchers who ever switch funding sources and those that do not, where the former group responds to technological opportunities or downstream subsidies but the latter does not. This is not impossible, but seems unlikely. At a minimum, we would expect to see attenuated results, but instead, we find null effects. We find a similar null placebo result for the career outcomes, but we have not reported them because the test creates a sub-sample that makes disclosure very challenging and restricts potential future disclosures. In a final version of the paper, this and other results can be reported.

In Section 4.2, we discussed the results of an event study using only large and temporary shocks. The results suggest that long-term funding changes do not explain the results, making the technological opportunities explanation less plausible. To confirm this, we control for long-term funding changes.

We expect that in the technological opportunities story, the negative effect of federal share on patenting should attenuate with controls for long term trends in the researcher's CFDA code. Appendix Table A.7 columns 3–4 show the opposite: controlling for changes in federal funding from six years ago to one year ago does not attenuate the estimates. By the same token, if long-term funding changes reflecting technological opportunities are the main driver, then using only one-time, large changes to federal funding should yield a smaller or noisier effect. We restrict the first stage changes to instances where year-to-year funding increased or decreased by more than 30% in a single CFDA code. The results, in Appendix Table A.7 columns 7–8, are slightly larger than the main findings and equally precise. This complements the results in Figures 3 and 4.

In a final test, we consider the possibility that researchers select into funding sources that are driven by the technological opportunities, in which case the individual patenting might be driven by the selection into CFDA funding codes. To address this concern, we control for the past patenting of researchers in Appendix Table A.7. Columns 5–6 show that the results are robust to controlling for the past three lags in the dependent variables.

4.5.4 Ordinary Least Squares Results

In this subsection, we examine the ordinary least squares (OLS) relationship between funding source and outcomes. Recall that the instrumental variables estimation is based on a set of marginal compliers who are pushed towards or away from federal funding as a result of changes in the supply of federal funding. In contrast, the mean relationship between federal funding and outcomes will primarily reflect selection into funding sources. An important factor is the greater prestige and perceived value to academics of federal funding. This may reflect the federal funding providing the researcher more control, more ability to do basic research, or a longer grant time horizon. As a result, we expect that on average higher quality and more senior researchers will have more federal funding. For these reasons, selection into funding should be associated with quite different effects than forced shifts among compliers.

The OLS relationship for patent outcomes is shown in Appendix Table A.2. The effects are in same direction as the IV and all significant at the .01 level, but are smaller in magnitude. This indicates that relative to people who select into more federal funding, those who are pushed in by the instrument are less likely to patent. That is, the OLS relationship governed by selection and the causal effects governed by compliers seem to reflect the same mechanism, but attenuated under selection.

For career outcomes, shown in Appendix Table A.3, the OLS relationships are quite different. In the IV results discussed Section 4.3 in the researchers pushed to federal funding by the instrument are more likely to become high-tech entrepreneurs, less likely to work for incumbents, and more likely to work at a university. In contrast, those who select into more federal funding are no more likely to become entrepreneurs (column 1), are more likely to work for incumbents (column 2), and are less likely to work for a university (column 3). These different OLS results for career outcomes are intuitive given the institutional facts about the two types of funding. Usually federally-funded teams are larger and have a higher ratio of staff and undergraduates. The former are less likely to become high-tech entrepreneurs, and the latter are less likely to work at a university and more likely to work for an incumbent. In other words, compliers with the instrument are more likely to be on margin for entering high-tech entrepreneurship.

5 Discussion

Our analysis sheds light on the role of federal funding in university research, and the tradeoffs between federal and industry sources. We consider the ways in which our results are consistent with or contradict several intuitive ways in which different types of funding might affect research outputs. One hypothesis is that one type of funding leads to more productive and commercially-relevant research. That is, one type of funding may be "better" overall, in which case it should lead to more innovation outputs generally. This is akin to the effects of having a better teacher on a child's outcome, independently of the child's own quality. The results indicate that the story is more nuanced than one type of funding simply pushing toward more productive research; while federal funding yields fewer patents, it yields more startups.

A second lens is the spectrum from basic to applied research, or moving downstream from the earliest stages of scientific inquiry toward commercial application of an existing invention. A natural prior is that federal funds will enable researchers to conduct basic research, while private sector funds will support more applied work. However, it is not clear that this is the case, especially when a researchers' field attracts both public and private funds. Some observers argue that federal agencies have shifted towards demanding more applied work and immediately commercially useful research outputs since the turn of the century.[23] Another factor is an increased focus on commercialization at the university level. Following the Bayh-Dole Act of 1980, it became much easier to patent and commercialize inventions that have government financial support, dramatically increasing the patenting rate at universities (Henderson, Jaffe and Trajtenberg 1998, Mowery, Sampat and Ziedonis 2002, Hausman 2017). This could drive all research to shift towards more applied work, regardless of funding source.

Many of the results support the hypothesis that federal funding pushes researchers towards doing more basic research, while private funding pushes researchers to do more applied work. In particular, a higher private share increases patenting activity; conditional on patenting, federal funding is associated with more citations per patent, which might be because they represent earlier stage technologies. Similarly, the lower rate of joining an incumbent firm from federal funding is consistent with more basic work being supported by federal grants.

The interpretation of the positive effect of federal share on high-tech entrepreneurship depends on whether earlier stage work will more likely be deployed by startups than by incumbents. Among others, Robinson (2008) and Babina and Howell (2019) argue that high-risk, high-reward ideas are more often optimally located in startups than in incumbent firms, as they benefit from focused, high-powered incentives. However, high-risk, high-reward ideas need not stem from more basic rather than applied research. For example, with more than $11 million in grant funds from the U.S. Department of Energy, MIT Professor Donald Sadoway and his PhD student David Bradwell (among other PhD students), developed a molten metal battery for large-scale grid energy storage. The team chose to bring

[23]E.g. See https://www.sciencemag.org/news/2017/03/data-check-us-government-share-basic-research-funding-falls-below-50 and https://www.nytimes.com/2005/04/02/technology/pentagon-redirects-its-research-dollars.html.

the battery to market via a startup named Ambri. David Bradwell served as co-founder, while Sadoway remained a full-time professor at MIT.[24] One of the government grants that enabled the research clearly had quite applied intentions: "the team is creating a community-scale electricity storage device using new materials and a battery design inspired by the aluminum production process known as smelting."[25] In sum, based on this and many other examples, it seems most intuitive to assume that more applied research will yield more startups. Therefore, the fact that federal funding dramatically increases the rate of high-tech entrepreneurship is not entirely consistent with the primary difference between federal and private funding being one of basic vs. applied research.

A third dimension is that the funding source may be relevant to the degree to which research outputs are privately appropriable and to who appropriates them. We expect that, if there is any difference along this dimension between the two types of funding, federally-funded research will be more open, encouraging cumulative innovation (Azoulay et al. 2019), while privately-funded research will be more often appropriated by the funder. The firm's case that funding university research is a NPV positive investment is obviously more straightforward if it has some rights to the output. Indeed, it is common for industry funders to have rights of first refusal to research findings, complex non-disclosure agreements, and some control over the direction of research (NAP 1993, McCluskey 2017).

Our results are quite consistent with the hypothesis that private funders push researchers towards work that the firm can appropriate. First, the standard way to protect inventions is to patent them, and we observe that private funding causes much more patenting. Federal research gives rise to more general patents, indicating that these outputs are more accessible to a broader range of future researchers. Consistent with this, 40% of the privately assigned patents we observe are assigned to their funder. Second, private funding leads to much less high-tech entrepreneurship, consistent with the funder appropriating research outputs and preventing them from being used by grant employees in startups. As federal funding has fewer strings attached, the funded intellectual property is freer to be used in a startup. Third, we find evidence that human capital created by a private grant is also often

[24] See https://ambri.com/company/, http://news.mit.edu/2016/battery-molten-metals-0112, and

[25] https://arpa-e.energy.gov/?q=slick-sheet-project/electroville-grid-scale-batteries

appropriated by the sponsor. This is consistent with a common perception that firms sponsor research in part to train future employees. We find that among individuals with private funding who subsequently work at any funder firm (~500 firms), 20% go to the firm that funded their own research.

In sum, our research shows that federal and private funding for university research are not perfect substitutes. Further, a shift away from federal funds and towards private funds leads to intellectual property and human capital that are more often appropriated by the sponsor and less often deployed in startups. Note, however, that our emphasis on the appropriation channel as most consistent with the data does not rule out the presence of other channels.

The policy implications of these findings are complex and beyond the scope of our work. However, universities are increasingly dependent on industry funding, and many actively recruit corporate research sponsors. Our results may be particularly relevant to these efforts. 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."[26] Universities have sought out more corporate funding in part because they have faced a secular decline in government funding for public universities, particularly at the state level.

An important aspect relevant to policy is whether federal funding crowds out private funding, along the lines of Goolsbee (1998). Our results cannot speak to whether or not this is the case, though existing work on R&D subsidies to private firms has generally not found evidence of crowding out (Hall and Van Reenen 2000, Bloom et al. 2002, Dechezleprêtre et al. 2016, Howell 2017, Balsmeier et al. 2018). In the small economic literature on public R&D investment, Moretti et al. (2019) find evidence that defense R&D "crowds in" private sector R&D. Nonetheless, if there is crowding out in our context, it should certainly be incorporated into any policy conclusions.

Our analysis points to larger knowledge spillovers from federal funding, because federal funding leads to more open research, while privately funded research appears to be more immediately appropriated by incumbent firms. However, we cannot evaluate the magnitude of knowledge

[26] See https://www.mics.ece.vt.edu/.

spillovers emerging from each source of funding. Private funding yields more patents, and while patents in one sense represent monopoly power, they are also disclosed to the public and when the term expires are in the public domain. These elements could potentially enable greater diffusion than, for example, a trade secret. It is also uncertain whether an invention commercialized in an incumbent firm will have more or less social benefits than if it were commercialized by a startup; similarly it is far from clear weather a researchers future work in universities provides more social befit than work that would be done an established firm. In sum, even if there are larger knowledge spillovers from federal funding, this does not lead to the conclusion that either source of funding is "better" from a social perspective.

Finally, our results are relevant to interpreting the implications of the Bayh-Dole Act of 1980, which enabled private firms to benefit more from funding university research. This is because most research draws on some federal funding, but post-Bayh-Dole, this does not preclude appropriation by a private funder. Aghion et al. (2008) show how this creates a tension. To the degree that academia is a second-best solution to the underinvestment problem identified by Nelson and Arrow, then greater appropriability and private sector funding of research in general should improve efficiency. At the same time, however, if research that would otherwise be left in the public domain is now privately appropriated, it will have fewer spillover benefits for other research. Our results indicate that private and federal funding push university researchers towards different means for commercializing successful innovations. Aghion et al. (2008) provide one mechanism, which is that private sector funding may reduce the researcher's control over what to study and how to study it, leading to greater emphasis on pursuing projects with more immediate economic value. In turn, this may have fewer spillovers for other scientists and therefore negative implications for cumulative innovation.

6 Conclusion

Using individual data on grant employees from 22 universities linked to patent and U.S. Census Bureau data, this paper offers the first causal analysis of the relative effects of federal and private university research funding on commercial innovation outputs. We instrument for an individual's source of funding with government-wide R&D expenditure shocks within a narrow field of study. This novel instrument provides a set of compliers who are pushed towards or away from federal funding. We show that neither technological opportunities, downstream subsidies, nor predictable trends confound causal interpretation.

We find that federal and private funding are not substitutes. A higher share of federal funding causes fewer but more general patents, much more high-tech entrepreneurship, a higher likelihood of remaining employed in academia, and a lower likelihood of joining an incumbent firm. These effects are largely inverted when we instrument for the share of private industry funding. The results consistently support the hypothesis that private funding leads to greater appropriation of intellectual property by incumbent firms. Privately funded research outputs are more often patented, while federally funded research outputs are more widely used (general), less likely to be patented, and more often spun out into startups.

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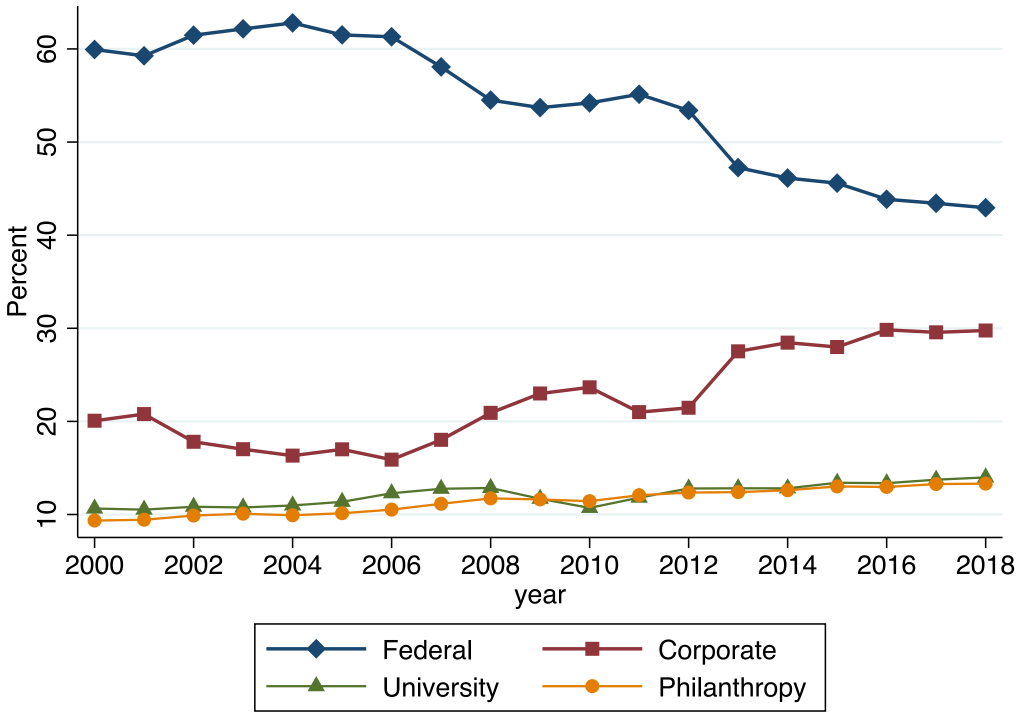
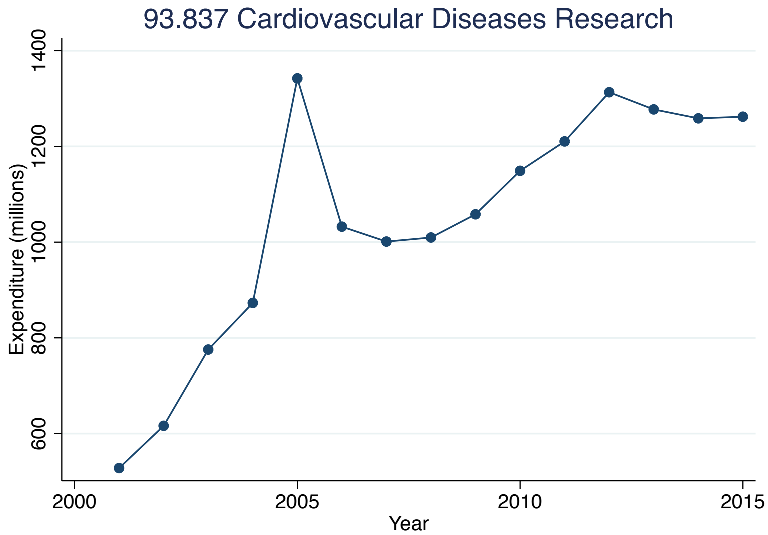
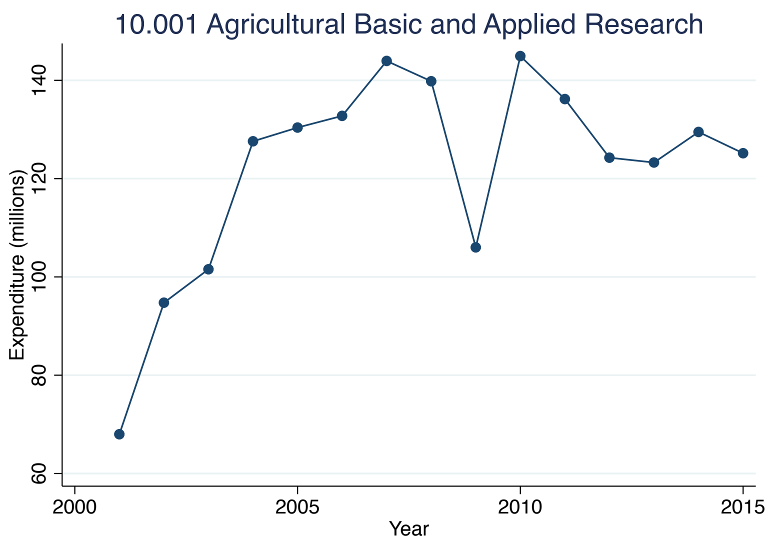
Figure 1. Sources of U.S. Research Funding, 2000-2018



Note: This figure shows the percent of total U.S. R&D funding from each of four sources – the federal government (Federal), the private sector (Corporate), Universities, and Philanthropy – in each year from 2000 to 2018. Data is from the NSF National Patterns of R&D Resources (https://ncses.nsf.gov/pubs/nsf19309).

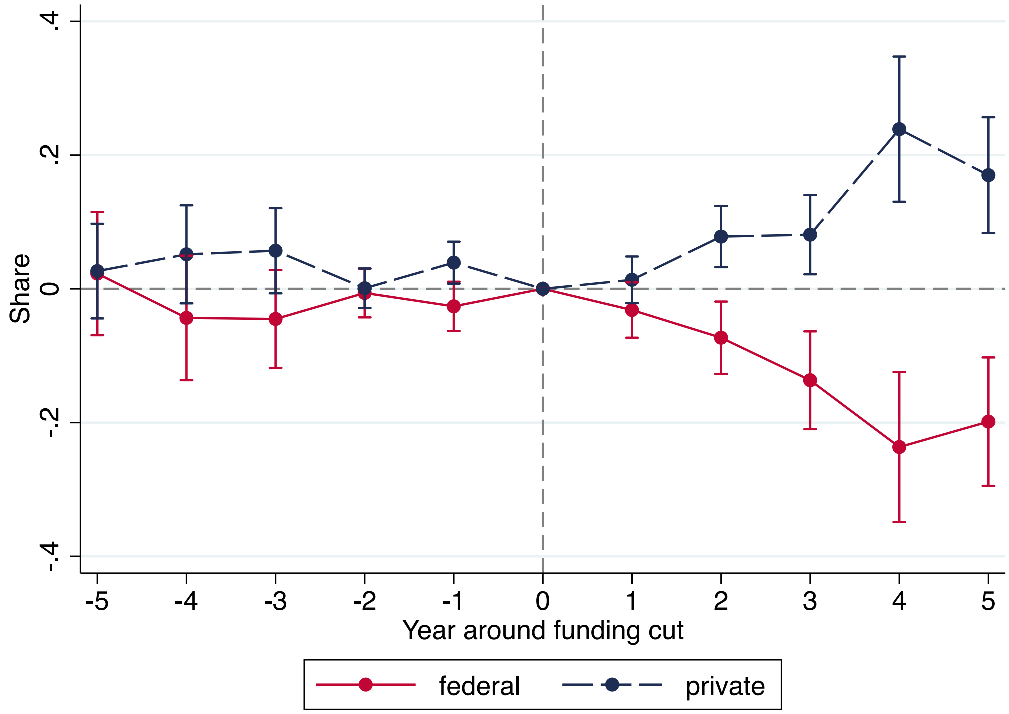
Figure 2. Examples of CFDA-level Funding Histories





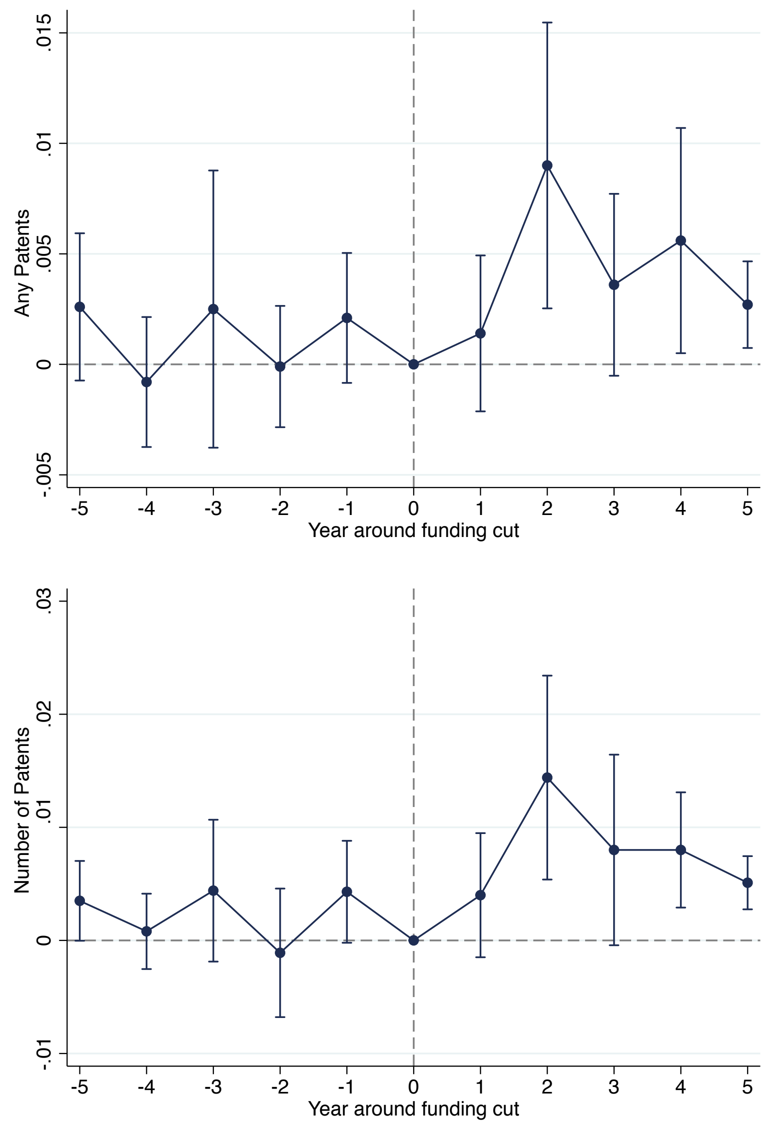
Note: This figure shows government-wide R&D expenditure in two CFDA codes, which provides the source of variation for the instrumental variables analysis. The top figure shows cardiovascular diseases research, a program at the National Institutes of Health. The bottom figure shows agricultural research, a program at the Department of Agriculture.

Figure 3. Event Study: Shares of Federal and Private Funding Around Large CFDA-level Shocks to Federal Funding



Note: This figure shows event study of changes in the shares of federal and private funding around large and temporary drops in the aggregate availability of CFDA-level federal funding at even time 0. The estimation equation is described in Section 4.5.

Figure 4. Event Study: Patenting Around Large CFDA-level Shocks to Federal Funding



Note: This figure shows patenting by researchers around large and temporary drops in the aggregate availability of CFDA-level federal funding at even time 0. The top figure shows changes in the probability of patenting. The bottom figure shows changes in the number of patents. The estimation equation is described in Section 4.5

Table 1. Summary Statistics

Panel A shows summary statistics for the UMETRICS data sample, Panel B for the patent data matched into the UMETRICS sample, and Panel C for the restricted-use US Census data matched with the UMETRICS sample. In all three panels, the sample is a person-year panel from 2001 through 2016. Share Federal is the share of the funding coming from Federal US Government sources. Share Private is the share of the funding coming from private sector. All patent measures are indicating whether the person was inventor of a patent (or patent of certain type) in current year. Statistics for patents with private assignee are based on a subs-ample of person-years with positive patents. High-tech Entrepreneur is an indicator for high-tech entrepreneurship (person at high-tech firm when firm age equals zero, in any of next three years starting from this year). Entrepreneur is an indicator for any type of entrepreneurship (at firm when firm age equal zero, in any of next three years starting from this year). Work for Incumbent is an indicator for person being at firm in next 3 years that is more than 5 years old, and not a university. Work for University is an indicator for person being at university in next 3 years starting from this year.

	Number of Observations	Mean	Median	Standard Deviation
Panel A: Umetrics				
Number of Universities	22			
Number of People	235,000			
Number of People with Federal Funding	230,000			
Number of People with Private Funding	58,000			
Number of People with Both Federal and Private Funding	54,000			
Faculty	571,000	0.192		
Graduate Students	571,000	0.292		
Staff	571,000	0.384		
Undergraduate Students	571,000	0.132		
Total Direct Expense$_{i,t}$	571,000	57,000	29,000	21,000
Overhead Charged$_{i,t}$	571,000	16,000	7,000	27,000
Share Federal$_{i,t-1}$	571,000	0.816	0	0.345
Share Private$_{i,t-1}$	571,000	0.111	1	0.276
Share Other$_{i,t-1}$	571,000	0.073	0	0.233
Number of CFDA Codes	571,000	2.19	2	1.86
Log-change Amount R&D$_{i,t-1}$	571,000	0.057	0.028	1.14
Log-change Amount R&D$_{i,t-2}$	571,000	0.092	0.050	1.11
Log(Expenditure$_{i,t}$)	571,000	9.95	10.27	1.64
Panel B: Patents				
Any Patents$_{i,t}$	571,000	0.0090		
Number of Patents$_{i,t}$	571,000	0.0117		
Any Cited Patents$_{i,t}$	571,000	0.0047		
Any Highly Cited Patents$_{i,t}$	571,000	0.0010		
Any Original Patents$_{i,t}$	571,000	0.0038		
Any General Patents$_{i,t}$	571,000	0.0016		
Any Patents with Private Assignee$_t$	571,000	0.0004		
Patents with Private Assignee$_t$	5,000	0.0403		

	Number of Observations	Mean	Quasi-Median	Standard Deviation
Panel C: Census				
Number of Unique Piks	149,000			
High-tech Entrepreneur$_{i,[t,t+2]}$	457,000	0.0074		
Entrepreneur$_{i,[t,t+2]}$	457,000	0.031		
Work for Young Firm$_{i,[t,t+2]}$	457,000	0.080		
Work for Young High-tech Firm$_{i,[t,t+2]}$	457,000	0.022		
Work for Incumbent Firm$_{i,[t,t+2]}$	457,000	0.553		
Work for Incumbent High-tech Firm$_{i,[t,t+2]}$	457,000	0.137		
Work for University$_{i,[t,t+2]}$	457,000	0.831		
Real Wage$_{i,t}$	457,000	56,000	36,000	70,000
Number of Jobs$_{i,t}$	457,000	1.19	1	0.501

Table 2. First Stage Effect of Total Federal R&D Funding in Field on Individual's Share of Funding

This Table reports the first stage results of the IV regression. The instrument is lagged researchers' weighted average of funding changes in CFDA programs as described in Section 2. The baseline sample is a person-year panel from 2001 through 2016 (consistent with the IV regressions). The dependent variables are share of total funding amount from federal government, private companies or other sources for a researcher in a given year. The last row reports the F-statistic for joint significance of the two instrumental variables. All regressions include university-by-year-by-field 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.

	Share Federal$_{i,t}$	Share Private$_{i,t}$	Share Other$_{i,t}$
	(1)	(2)	(3)
Log-change Amount R&D$_{i,t-1}$	0.0038***	-0.0026***	-0.0011***
	(0.0003)	(0.0003)	(0.0002)
Log-change Amount R&D$_{i,t-2}$	0.0040***	-0.0029***	-0.0010***
	(0.0003)	(0.0002)	(0.0002)
Log(Expenditure$_{i,t-1}$)	0.0063***	0.0040***	-0.0102***
	(0.0005)	(0.0004)	(0.0004)
University$\times$Year$\times$Field FE	Yes	Yes	Yes
Number of Observations	571,000	571,000	571,000
Mean of Dependent Variable	0.816	0.111	0.073
Adjusted R-squared	0.156	0.101	0.246
F-statistic	117	93.7	25.3

Table 3. Second Stage IV Effect of the Share of Federal Funding on Patent Outcomes

Table reports second stage results of the IV regressions of the reduction in federal funding on researcher's innovation outcomes. The baseline sample is a person-year panel from 2001 through 2016. The dependent variables are innovation outcomes indicating whether the person is an inventor of a patent (or of a patent of certain type) in current year. The key independent variable, Share Federal, is the share of the funding coming from Federal US Government sources. Share Federal is instrumented with funding shocks coming from the aggregate changes in federal funding of fields (CFDA codes) in which the researcher received funding in the previous two years. First-stage F-statistics indicate the instruments to be strong. Standard errors are clustered at the person level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Any Patents$_{i,t}$	Number of Patents$_{i,t}$	Any Highly Cited Patents$_{i,t}$	Any Original Patents$_{i,t}$	Any General Patents$_{i,t}$	Any Patents with Private Assignee$_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
Share Federal$_{i,t-1}$	-0.0509***	-0.0803***	-0.0015	-0.0168*	0.0107*	-0.0086***
	(0.0140)	(0.0200)	(0.0047)	(0.0094)	(0.0060)	(0.0028)
Log(Expenditure$_{i,t-1}$)	0.0034***	0.0051***	0.0004***	0.0015***	0.0005***	0.0002***
	(0.0002)	(0.0004)	(0.0001)	(0.0001)	(0.0001)	(0.0000)
University$\times$Year$\times$Field FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	571,000	571,000	571,000	571,000	571,000	571,000
Mean of Dependent Variable	0.0090	0.0117	0.0010	0.0038	0.0016	0.0004
F-statistic	117	117	117	117	117	117

Table 4. Patent Characteristics by Funding Source

This table shows summary statistics about the patent variables, comparing averages for patents of researchers with federal funding, private funding, and all other types of funding (including state government, university, and nonprofit foundations). The differences between the mean for federally and privately funded are statistically significant with t-statistics greater than 2.5 for all variables except originality. The first row contains the sample size (number of patents) for each group.

Funding Source:	Federal	Private	Other
# of Patents	7202	989	282
Mean Originality	0.322	0.268	0.32
Mean Generality	0.195	0.126	0.113
Mean Citation	0.819	0.352	0.305
% of Assignees that are Private Firm	4.4	4.8	6.7

Table 5. Second Stage IV Effect of Share of Federal Funding on Patent Outcomes by Occupation

Table reports second stage results of the IV regressions of the reduction in federal funding on researcher's innovation outcomes by occupation: faculty, graduate students, staff, and undergraduate students. The baseline sample is a person-year panel from 2001 through 2016. The dependent variables are innovation outcomes indicating whether the person is inventor of a patent (or of patent of certain type) in current year. The key independent variable, Share Federal, is the share of the funding coming from Federal US Government sources. Share Federal is instrumented with funding shocks coming from the aggregate changes in federal funding of fields (CFDA codes) in which the researcher received funding in the previous two years. First-stage F-statistics indicate the instruments to be strong. Standard errors are clustered at the person level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Faculty		Graduate Students		Undergraduate Students		Staff	
	Any Patents$_{i,t}$	Number of Patents$_{i,t}$	Any Patents$_{i,t}$	Number of Patents$_{i,t}$	Any Patents$_{i,t}$	Number of Patents$_{i,t}$	Any Patents$_{i,t}$	Number of Patents$_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share Federal$_{i,t-1}$	-0.1005	-0.2095**	-0.0485	-0.0465	0.0017	0.0036	0.0147	0.0156
	(0.0622)	(0.0993)	(0.0355)	(0.0429)	(0.0135)	(0.0198)	(0.0199)	(0.0209)
Log(Expenditure$_{i,t-1}$)	0.0094***	0.0167***	0.0028***	0.0031***	0.0006**	0.0007*	0.0004	0.0005
	(0.0010)	(0.0020)	(0.0008)	(0.0010)	(0.0003)	(0.0004)	(0.0004)	(0.0004)
University$\times$Year$\times$Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	110,000	110,000	165,000	165,000	220,000	220,000	76,000	76,000
F-statistic	14.79	14.79	25.6	25.6	57.6	57.6	41.9	41.9

Table 6. Second Stage IV Effect of the Share of Federal Funding on Career Outcomes

Table reports second stage results of the IV regressions of the reduction in federal funding on researcher's career outcomes. The baseline sample is a person-year panel from 2001 through 2016. The dependent variables are measured from the restricted-use US Census data matched with the UMETRICS data. High-tech Entrepreneur is an indicator for high-tech entrepreneurship (person at high-tech firm when firm age equals zero, in any of next three years starting from this year). Work for Incumbent is an indicator for person being at firm in next 3 years that is more than 5 years old, and not a university. Work for University is an indicator for person being at university in next 3 years starting from this year. The key independent variable, Share Federal, is the share of the funding coming from Federal US Government sources. Share Federal is instrumented with funding shocks coming from the aggregate changes in federal funding of fields (CFDA codes) in which the researcher received funding in the previous two years. First-stage F-statistics indicate the instruments to be strong. Standard errors are clustered at the person level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	High-tech Entrepreneur$_{i,[t,t+2]}$	Work for Incumbent Firm$_{i,[t,t+2]}$	Work for University$_{i,[t,t+2]}$
	(1)	(2)	(3)
Share Federal$_{i,t-1}$	0.0449**	-0.9710***	0.5287***
	(0.0211)	(0.1212)	(0.0859)
Log(Expenditure$_{i,t-1}$)	0.0002***	-0.0083***	0.0018***
	(0.0000)	(0.0003)	(0.0002)
University$\times$Year$\times$Field FE	Yes	Yes	Yes
Number of Observations	457,000	457,000	457,000
Mean of Dependent Variable	0.0074	0.553	0.831
F-statistic	112	112	112

Table 7. Second Stage IV Effect of Share of Federal Funding on Career Outcomes by Occupation

Table reports second stage results of the IV regressions of the reduction in federal funding on researcher's innovation outcomes by occupation: faculty, graduate students, staff, and undergraduate students. The baseline sample is a person-year panel from 2001 through 2016. The dependent variables are measured from the restricted-use US Census data matched with the UMETRICS data. High-tech Entrepreneur is an indicator for high-tech entrepreneurship (person at high-tech firm when firm age equals zero, in any of next three years starting from this year). Work for Incumbent is an indicator for person being at firm in next 3 years that is more than 5 years old, and not a university. Work for University is an indicator for person being at university in next 3 years starting from this year. The key independent variable, Share Federal, is the share of the funding coming from Federal US Government sources. Share Federal is instrumented with funding shocks coming from the aggregate changes in federal funding of fields (CFDA codes) in which the researcher received funding in the previous two years. First-stage F-statistics indicate the instruments to be strong. Standard errors are clustered at the person level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Graduate and Undergraduate Students

	Graduate Student			Undergraduate Students		
	High-tech Entrepreneur$_{i,[t,t+2]}$	Work for Incumbent Firm$_{i,[t,t+2]}$	Work for University$_{i,[t,t+2]}$	High-tech Entrepreneur$_{i,[t,t+2]}$	Work for Incumbent Firm$_{i,[t,t+2]}$	Work for University$_{i,[t,t+2]}$
	(1)	(2)	(3)	(4)	(5)	(6)
Share Federal$_{i,t-1}$	0.0599*	-0.4793***	0.2722**	0.0818	-1.0049***	0.5194**
	(0.0319)	(0.1478)	(0.1072)	(0.0614)	(0.2840)	(0.2508)
Log(Expenditure$_{i,t-1}$)	0.0002***	-0.0012***	-0.0043***	0.0004	-0.0055***	-0.0067***
	(0.0000)	(0.0002)	(0.0002)	(0.0003)	(0.0012)	(0.0011)
University×Year×Field FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	260,000	260,000	260,000	70,000	70,000	70,000
F-statistic	59	59	59	21	21	21

Panel B. Faculty and Staff

	Faculty			Staff		
	High-tech Entrepreneur$_{i,[t,t+2]}$	Work for Incumbent Firm$_{i,[t,t+2]}$	Work for University$_{i,[t,t+2]}$	High-tech Entrepreneur$_{i,[t,t+2]}$	Work for Incumbent Firm$_{i,[t,t+2]}$	Work for University$_{i,[t,t+2]}$
	(1)	(2)	(3)	(4)	(5)	(6)
Share Federal$_{i,t-1}$	-0.0040	-0.2989**	0.0239	0.0129	-0.1412	-0.0240
	(0.0274)	(0.1501)	(0.0959)	(0.0261)	(0.1802)	(0.1313)
Log(Expenditure$_{i,t-1}$)	0.0001	0.0007	0.0004	-0.0000	-0.0097***	0.0009
	(0.0001)	(0.0006)	(0.0004)	(0.0001)	(0.0008)	(0.0006)
University×Year×Field FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	87,500	87,500	87,500	45,000	45,000	45,000
F-statistic	24	24	24	34	34	34

Table 8. Second Stage IV Effect of the Share of Private Funding on Patent Outcomes

Table reports second stage results of the IV regressions of the shift from federal to private funding on researcher's innovation outcomes. The baseline sample is a person-year panel from 2001 through 2016. The dependent variables are innovation outcomes indicating whether the person is an inventor of a patent (or of a patent of certain type) in current year. The key independent variable, Share Private, is the share of the funding coming from private sources. Share Private is instrumented with funding shocks coming from the aggregate changes in federal funding of fields (CFDA codes) in which the researcher received funding in the previous two years. First-stage F-statistics indicate the instruments to be strong. Standard errors are clustered at the person level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Any Patents$_{i,t}$	Number of Patents$_{i,t}$	Any Highly Cited Patents$_{i,t}$	Any Original Patents$_{i,t}$	Any General Patents$_{i,t}$	Any Patents with Private Assignee$_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
Share Private$_{i,t-1}$	0.0746***	0.1174***	0.0024	0.0240*	-0.0159*	0.0126***
	(0.0207)	(0.0297)	(0.0070)	(0.0139)	(0.0088)	(0.0041)
Log(Expenditure$_{i,t-1}$)	0.0028***	0.0041***	0.0004***	0.0013***	0.0006***	0.0001***
	(0.0002)	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.0000)
University$\times$Year$\times$Field FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	571,000	571,000	571,000	571,000	571,000	571,000
Mean of Dependent Variable	0.0090	0.0117	0.0010	0.0038	0.0016	0.0004
F-statistic	93.7	93.7	93.7	93.7	93.7	93.7

Table 9. Second Stage IV Effect of the Share of Private Funding on Career Outcomes

Table reports second stage results of the IV regressions of the shift from federal to private funding on researcher's career outcomes. The baseline sample is a person-year panel from 2001 through 2016. The dependent variables are measured from the restricted-use US Census data matched with the UMETRICS data. High-tech Entrepreneur is an indicator for high-tech entrepreneurship (person at high-tech firm when firm age equals zero, in any of next three years starting from this year). Work for Incumbent is an indicator for person being at firm in next 3 years that is more than 5 years old, and not a university. Work for University is an indicator for person being at university in next 3 years starting from this year. The key independent variable, Share Private, is the share of the funding coming from private sources. Share Private is instrumented with funding shocks coming from the aggregate changes in federal funding of fields (CFDA codes) in which the researcher received funding in the previous two years. First-stage F-statistics indicate the instruments to be strong. Standard errors are clustered at the person level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	High-tech Entrepreneur$_{i,[t,t+2]}$	Work for Incumbent Firm$_{i,[t,t+2]}$	Work for University$_{i,[t,t+2]}$
	(1)	(2)	(3)
Share Private$_{i,t-1}$	-0.0762**	1.0929***	-0.6845***
	(0.0325)	(0.1790)	(0.1317)
Log(Expenditure$_{i,t-1}$)	0.0001***	-0.0075***	0.0014***
	(0.0000)	(0.0002)	(0.0002)
University×Year×Field FE	Yes	Yes	Yes
Number of Observations	457,000	457,000	457,000
Mean of Dependent Variable	0.0074	0.553	0.831
F-statistic	74	74	74

Table 10. Robustness. Second Stage IV Effect of the Total Expenditures on Patent and Career Outcomes

Table reports second stage results of the IV regressions of the total expenditures on researcher's key innovation and career outcomes. The baseline sample is a person-year panel from 2001 through 2016. In columns 1–2, the dependent variables are innovation outcomes indicating whether the person is an inventor of a patent (or the number of patents) in current year. In columns 3–5, the dependent variables are career outcomes: High-tech Entrepreneur is an indicator for high-tech entrepreneurship (person at high-tech firm when firm age equals zero, in any of next three years starting from this year); Work for Incumbent is an indicator for person being at firm in next 3 years that is more than 5 years old, and not a university; Work for University is an indicator for person being at university in next 3 years starting from this year. The key independent variable, Expenditure, is the log of the researcher's past year total expenditures from all sources. Log(Expenditure) is instrumented with funding shocks coming from the aggregate changes in federal funding of fields (CFDA codes) in which the researcher received funding in the previous two years. First-stage F-statistics indicate the instruments to be strong. Standard errors are clustered at the person level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Patent Outcomes		Career Outcomes		
	Any Patents$_{i,t}$	Number of Patents$_{i,t}$	High-tech Entrepreneur$_{i,[t,t+2]}$	Work for Incumbent Firm$_{i,[t,t+2]}$	Work for University$_{i,[t,t+2]}$
	(1)	(2)	(3)	(4)	(5)
Log(Expenditure$_{i,t-1}$)	-0.0020	-0.0036*	-0.0016	0.0994***	-0.0458***
	(0.0013)	(0.0018)	(0.0014)	(0.0109)	(0.0071)
University×Year×Field FE	Yes	Yes	Yes	Yes	Yes
Number of Observations	571,000	571,000	457,000	457,000	457,000
Mean of Dependent Variable	0.0090	0.0117	0.0074	0.553	0.831
F-statistic	551	551	94	94	94
Mean effect of 10% change	-0.021	-0.029	-0.021	0.017	-0.005

A Appendix

Table A.1. Second Stage IV Effect of the Share of Federal Funding on Additional Career Outcomes

Table reports second stage results of the IV regressions of the reduction in federal funding on researcher's career outcomes. The baseline sample is a person-year panel from 2001 through 2016. The dependent variables are measured from the restricted-use US Census data matched with the UMETRICS data. Entrepreneur is an indicator for any type of entrepreneurship (at firm when firm age equal zero, in any of next three years starting from this year). Work for Young (High-tech) Firm is an indicator for person being at (a high-tech) firm in next 3 years that is no more than 5 years old, but has an age greater than zero. Work for Incumbent High-tech Firm is an indicator for person being at a high-tech firm in next 3 years that is more than 5 years old, and not a university. Log(Wage) is the log of real wage in 2014 dollars, where wage is the maximum wage revived from any single sorce. The key independent variable, Share Federal, is the share of the funding coming from Federal US Government sources. Share Federal is instrumented with funding shocks coming from the aggregate changes in federal funding of fields (CFDA codes) in which the researcher received funding in the previous two years. First-stage F-statistics indicate the instruments to be strong. Standard errors are clustered at the person level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Entrepreneur$_{i,[t,t+2]}$	Work for Young Firm$_{i,[t,t+2]}$	Work for Young High-tech Firm$_{i,[t,t+2]}$	Work for Incumbent High-tech Firm$_{i,[t,t+2]}$	Log(Wage$_{i,t}$)
	(1)	(2)	(3)	(4)	(5)
Share Federal$_{i,t-1}$	-0.0801**	-0.2095***	0.0772**	-0.0054	0.7573
	(0.0398)	(0.0619)	(0.0345)	(0.0726)	(0.4639)
Log(Expenditure$_{i,t-1}$)	-0.0010***	-0.0027***	0.0772**	-0.0008***	0.0616***
	(0.0001)	(0.0001)	(0.0345)	(0.0002)	(0.0010)
University×Year×Field FE	Yes	Yes	Yes	Yes	Yes
Number of Observations	457,000	457,000	457,000	457,000	457,000
Mean of Dependent Variable	0.031	0.08	0.022	0.137	10.04
F-statistic	112	112	112	112	112

Table A.2. OLS Effect of the Share of Federal Funding on Patent Outcomes

Table reports OLS regressions of the reduction in federal funding on researcher's innovation outcomes. The baseline sample is a person-year panel from 2001 through 2016. The dependent variables are innovation outcomes indicating whether the person is an inventor of a patent (or of a patent of certain type) in current year. The key independent variable, Share Federal, is the share of the funding coming from Federal US Government sources. Standard errors are clustered at the person level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Any Patents$_{i,t}$	Number of Patents$_{i,t}$	Any Highly Cited Patents$_{i,t}$	Any Original Patents$_{i,t}$	Any General Patents$_{i,t}$	Any Patents with Private Assignee$_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
Share Federal$_{i,t-1}$	-0.0015***	-0.0030***	-0.0002**	-0.0010***	-0.0003**	-0.0005***
	(0.0003)	(0.0006)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Log(Expenditure$_{i,t-1}$)	0.0025***	0.0038***	0.0003***	0.0011***	0.0004***	0.0001***
	(0.0001)	(0.0002)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
University×Year×Field FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	764,000	764,000	764,000	764,000	764,000	764,000
Mean of Dependent Variable	0.0090	0.0117	0.0010	0.0038	0.0016	0.0004
Adjusted R-squared	0.014	0.012	0.003	0.007	0.008	0.002

Table A.3. OLS Effect of the Share of Federal Funding on Career Outcomes

Table reports OLS regressions of the reduction in federal funding on researcher's career outcomes. The baseline sample is a person-year panel from 2001 through 2016. The dependent variables are measured from the restricted-use US Census data matched with the UMETRICS data. High-tech Entrepreneur is an indicator for high-tech entrepreneurship (person at high-tech firm when firm age equals zero, in any of next three years starting from this year). Work for Incumbent is an indicator for person being at firm in next 3 years that is more than 5 years old, and not a university. Work for University is an indicator for person being at university in next 3 years starting from this year. The key independent variable, Share Federal, is the share of the funding coming from Federal US Government sources. Standard errors are clustered at the person level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	High-tech Entrepreneur$_{i,[t,t+2]}$	Work for Incumbent Firm$_{i,[t,t+2]}$	Work for University$_{i,[t,t+2]}$
	(1)	(2)	(3)
Share Federal$_{i,t-1}$	-0.0008	0.0369***	-0.0528***
	(0.0006)	(0.0029)	(0.0020)
Log(Expenditure$_{i,t-1}$)	0.0001***	-0.0070***	0.0011***
	(0.0000)	(0.0002)	(0.0001)
University×Year×Field FE	Yes	Yes	Yes
Number of Observations	457,000	457,000	457,000
Mean of Dependent Variable	0.0074	0.553	0.831
Adjusted R-squared	0.003	0.293	0.065

Table A.4. Robustness. Second Stage IV Effect of the Share of Federal Funding on Patent and Career Outcomes: Cluster Standard Errors at University-By-Field Level

Table shows that the second stage results of the IV regressions of the reduction in federal funding on researcher's outcomes are robust to clustering standard errors at university-by-field level. The baseline sample is a person-year panel from 2001 through 2016. In columns 1–6, the dependent variables are innovation outcomes indicating whether the person is an inventor of a patent (or of a patent of certain type) in current year. In columns 7–9, the dependent variables are career outcomes: High-tech Entrepreneur is an indicator for high-tech entrepreneurship (person at high-tech firm when firm age equals zero, in any of next three years starting from this year); Work for Incumbent is an indicator for person being at firm in next 3 years that is more than 5 years old, and not a university; Work for University is an indicator for person being at university in next 3 years starting from this year. The key independent variable, Share Federal, is the share of the funding coming from Federal US Government sources. Share Federal is instrumented with funding shocks coming from the aggregate changes in federal funding of fields (CFDA codes) in which the researcher received funding in the previous two years. First-stage F-statistics indicate the instruments to be strong. Standard errors are clustered at the person level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Patent Outcomes						Career Outcomes		
	Any Patents$_{i,t}$	Number of Patents$_{i,t}$	Any Highly Cited Patents$_{i,t}$	Any Original Patents$_{i,t}$	Any General Patents$_{i,t}$	Any Patents with Private Assignee$_{i,t}$	High-tech Entrepreneur$_{i,[t,t+2]}$	Work for Incumbent Firm$_{i,[t,t+2]}$	Work for University$_{i,[t,t+2]}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Share Federal$_{i,t-1}$	-0.0509**	-0.0803**	-0.0015	-0.0168	0.0107	-0.0086*	0.0449**	-0.9710**	0.5287*
	(0.0258)	(0.0370)	(0.0034)	(0.0127)	(0.0079)	(0.0049)	(0.0207)	(0.3969)	(0.3051)
Log(Expenditure$_{i,t-1}$)	0.0034***	0.0051***	0.0004***	0.0015***	0.0005**	0.0002	0.0002***	-0.0083***	0.0018**
	(0.0008)	(0.0013)	(0.0001)	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0016)	(0.0008)
University × Year × Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	571,000	571,000	571,000	571,000	571,000	571,000	457,000	457,000	457,000
Mean of Dependent Variable	0.0090	0.0117	0.0010	0.0038	0.0016	0.0004	0.0074	0.553	0.831
F-statistic	26.3	26.3	26.3	26.3	26.3	26.3	19	19	19

Table A.5. Robustness. Alternative Controls in Second Stage IV Effect of the Share of Federal Funding on Career Outcomes

Table shows that the second stage results of the IV regressions of the reduction in federal funding on researcher's career outcomes are robust to using different control variables.The baseline sample is a person-year panel from 2001 through 2016. The dependent variables are measured from the restricted-use US Census data matched with the UMETRICS data. High-tech Entrepreneur is an indicator for high-tech entrepreneurship (person at high-tech firm when firm age equals zero, in any of next three years starting from this year). Work for Incumbent is an indicator for person being at firm in next 3 years that is more than 5 years old, and not a university. Work for University is an indicator for person being at university in next 3 years starting from this year. The key independent variable, Share Federal, is the share of the funding coming from Federal US Government sources. Share Federal is instrumented with funding shocks coming from the aggregate changes in federal funding of fields (CFDA codes) in which the researcher received funding in the previous two years. First-stage F-statistics indicate the instruments to be strong. Standard errors are clustered at the person level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	High-tech Entrepreneur$_{i,[t,t+2]}$			Work for Incumbent Firm$_{i,[t,t+2]}$			Work for University$_{i,[t,t+2]}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Share Federal$_{i,t-1}$	0.0461**	0.0414*	0.0431**	-0.9421***	-1.1235***	-0.8969***	0.4400***	0.7300***	0.5129***
	(0.0211)	(0.0232)	(0.0208)	(0.1203)	(0.1398)	(0.1176)	(0.0834)	(0.1013)	(0.0845)
Log-change Expenditure$_{i,t-1}$	-0.0002***			0.0030***			0.0043***		
	(0.0000)			(0.0002)			(0.0002)		
Log(Expenditure$_{i,t-1}$)		0.0001***			-0.0044***			-0.0015***	
		(0.0000)			(0.0002)			(0.0002)	
Log(Expenditure$_{i,t-2}$)		0.0001*			-0.0067***			0.0056***	
		(0.0001)			(0.0004)			(0.0003)	
University$\times$Year$\times$Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	457,000	457,000	457,000	457,000	457,000	457,000	457,000	457,000	457,000
Mean of Dependent Variable	0.0074	0.0074	0.0074	0.553	0.553	0.553	0.831	0.831	0.831
F-statistic	112	94	114	112	94	114	112	94	114

Table A.6. Robustness. Alternative Controls in Second Stage IV Effect of the Share of Federal Funding on Patent Outcomes

Table shows that the second stage results of the IV regressions of the reduction in federal funding on researcher's innovation outcomes are robust to using different control variables. The baseline sample is a person-year panel from 2001 through 2016. In both panels, he dependent variables are innovation outcomes indicating whether the person is an inventor of a patent (or of a patent of certain type) in current year. The key independent variable, Share Federal, is the share of the funding coming from Federal US Government sources. Share Federal is instrumented with funding shocks coming from the aggregate changes in federal funding of fields (CFDA codes) in which the researcher received funding in the previous two years. In columns 1, 4, and 7, we control for changed in the researcher's total expenditures from *t-1* to *t*. In columns 2, 5, and 8, we control for two lags of the researcher's total expenditure. Columns 3, 6, and 9 do not control for the total expenditures. First-stage F-statistics indicate the instruments to be strong. Standard errors are clustered at the person level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A

	Any Patents$_{i,t}$			Number of Patents$_{i,t}$			Any Highly Cited Patents$_{i,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Share Federal$_{i,t-1}$	-0.0260**	-0.0454***	-0.0207	-0.0379**	-0.0726***	-0.0347*	0.0025	-0.0007	0.0019
	(0.0129)	(0.0142)	(0.0128)	(0.0181)	(0.0202)	(0.0179)	(0.0045)	(0.0048)	(0.0044)
Log-change Expenditure$_{i,t-1}$	-0.0006***			-0.0009***			-0.0001***		
	(0)			(0.0001			(0)		
Log(Expenditure$_{i,t-1}$)		0.0026***			0.0041***			0.0003***	
		(0.0002)			(0.0004)			(0.0001)	
Log(Expenditure$_{i,t-2}$)		0.0005***			0.0006***			0.0001***	
		(0)			(0.0001)			(0)	
University×Year×Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	565,000	565,000	571,000	565,000	565,000	571,000	565,000	565,000	571,000
Mean of Dependent Variable	0.0090	0.0090	0.0090	0.0117	0.0117	0.0117	0.0010	0.0010	0.0010
F-statistic	131	131	131	131	131	131	131	131	131

Panel B

	Any Original Patents$_{i,t}$			Any General Patents$_{i,t}$			Any Patents with Private Assignee$_{i,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Share Federal$_{i,t-1}$	-0.0014	-0.0139	-0.0038	0.0162***	0.0122**	0.0151***	-0.0066***	-0.0084***	-0.0068***
	(0.0089	(0.0096)	(0.0088	(0.0057)	(0.0061)	(0.0057)	(0.0025)	(0.0028)	(0.0025)
Log-change Expenditure$_{i,t-1}$	-0.0003***			-0.0001***			-0.0000***		
	(0)			(0)			(0)		
Log(Expenditure$_{i,t-1}$)		0.0011***			0.0003***			0.0002***	
		(0.0001)			(0.0001)			(0)	
Log(Expenditure$_{i,t-2}$)		0.0002***			0.0001***			0.0000***	
		(0)			(0)			(0)	
University×Year×Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	565,000	565,000	571,000	565,000	565,000	571,000	565,000	565,000	571,000
Mean of Dependent Variable	0.0038	0.0038	0.0038	0.0016	0.0016	0.0016	0.0004	0.0004	0.0004
F-statistic	131	131	131	131	131	131	131	131	131

Table A.7. Robustness. Second Stage IV Effect of the Share of Federal Funding on Patent Outcomes: Placebo Test, Controls for Long-term Trends, Use Large Federal Funding Shocks, and Control for Past Values of Dependent Variables

Table reports robustness tests for the second stage results of the IV regressions of the reduction in federal funding on researcher's key innovation outcomes. The baseline sample is a person-year panel from 2001 through 2016. The dependent variables are innovation outcomes indicating whether the person is an inventor of a patent (or the number of patents) in current year. In columns 1–2, the sample is all researchers who receive 100% of their funding from the federal government in every year observed in the data, and the independent variables, Log-change Amount R&D are two lags of the researcher weighted average of funding changes in CFDA programs as described in Section 2, and used as the instruments (for share federal) measuring funding shocks coming from the aggregate changes in federal funding of fields (CFDA codes) in which the researcher received funding in the previous two years. In columns 3–8, the independent variable, Share Federal, is the share of the funding coming from Federal US Government sources. Share Federal is instrumented with funding shocks (the two lags of Log-change Amount R&D) coming from the aggregate changes in federal funding of fields (CFDA codes) in which the researcher received funding in the previous two years. Columns 3–4 include controls for the long-term trends in CFDA funding categories (defined as funding changes from six years ago to one year ago) in which the researcher had funding as of a year ago. Columns 5–6 are only estimated off the CFDA changes that are at least 30% in absolute value; the changes with smaller than 30% change are set to zero. Columns 7–8 include controls for three lags of the dependent variable. In columns 3–8, the estimates of all control variables are suppressed for readability. First-stage F-statistics indicate the instruments to be strong. Standard errors are clustered at the person level, and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Placebo: Non-Switchers		Control for Long-term Trends in Shocks		Large Federal Funding Shocks		Control for Past Patenting	
	Any Patents$_{i,t}$	Number of Patents$_{i,t}$	Any Patents$_{i,t}$	Number of Patents$_{i,t}$	Any Patents$_{i,t}$	Number of Patents$_{i,t}$	Any Patents$_{i,t}$	Number of Patents$_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log-change Amount R&D$_{i,t-1}$	-0.0001	-0.0001						
	(0.0001)	(0.0001)						
Log-change Amount R&D$_{i,t-2}$	-0.0001	-0.0001						
	(0.0001)	(0.0001)						
Log(Expenditure$_{i,t-1}$)	0.0011***	0.0013***	0.0034***	0.0051***	0.0034***	0.0051***	0.0017***	0.0018***
	(0.0001)	(0.0001)	(0.0002)	(0.0004)	(0.0002)	(0.0004)	(0.0001)	(0.0002)
Share Federal$_{i,t-1}$			-0.0579***	-0.0883***	-0.0519***	-0.0810***	-0.0328***	-0.0377**
			(0.0164)	(0.0232)	(0.0144)	(0.0205)	(0.0122)	(0.0162)
University×Year×Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	282,000	282,000	552,000	552,000	571,000	571,000	557,000	557,000
Mean of Dependent Variable	0.0090	0.0117	0.0090	0.0117	0.0090	0.0117	0.0090	0.0117
F-statistic	NA	NA	81	81	111	111	110	110