Does Funding Source Matter for University R&D?

The Effect of Government vs. Industry Grants*

Tania Babina Alex Xi He Sabrina T. Howell

Elisabeth Ruth Perlman Joseph Staudt

March 15, 2020

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.

Keywords: R&D, Science, Universities, Innovation, Entrepreneurship
JEL classification: O3, G18, G38, I2

*Babina: Columbia University, tania.babina@gsb.columbia.edu. He: University of Maryland, ahe@rhsmith.umd.edu. Howell: NYU & NBER, sabrina.howell@nyu.edu. Perlman: US Census Bureau, elisabeth.perlman@census.gov. Staudt: US Census Bureau, joseph.staudt@census.gov. We thank Lauren Cohen, Daniel Gross, Scott Kominers, Natsuko Nicholls, Jason Owen-Smith, and Beth Uberseder, as well as participants at the NSF Future of IP conference. For helpful research assistance, we thank Belinda Chen and Jun Wong. Howell's research on this project was in part funded by the NBER Science of Science Program, sponsored by the Sloan Foundation. This paper uses data from the U.S. Census Bureau. Any views expressed are those of the authors and not those of the U.S. Census Bureau. The Census Bureau's Disclosure Review Board and Disclosure Avoidance Officers have reviewed this data product for unauthorized disclosure of confidential information and have approved the disclosure avoidance practices applied to this release. (DRB Approval Number CBDRB-FY20-152).

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 property to be privately appropriated,

[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.

private funding may lead to fewer knowledge spillovers from university research.[3] There is evidence – again from the medical sciences – that long term incentives matter; Budish et al. (2015) document that private R&D investment in drugs is more sensitive than public investment to the time required for commercialization, and Azoulay et al. (2011) show that rewarding long term success while tolerating short term failure leads to higher impact research.

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 that neither technological trends, downstream subsidies, nor predictability confound estimation. An

[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."

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, which suggests that federally-funded research is less appropriable. When we split the sample by occupation, we find that faculty and 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 60% 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 much 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 strongest among graduate and undergraduate students, and the effect among staff is zero. Undergraduates are mostly responsible for the negative effect on working at an incumbent firm and 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 and reduces the chances of becoming a high-tech entrepreneur by 13% of the mean.

Several key robustness tests validate the main results. First, if technological opportunities or downstream subsidies explained the effects, these factors should also impact researchers who do not switch between federal and private sources. Instead, we find no effects of federal funding changes on these non-switchers. In addition, if technological opportunities drove the results, future funding changes should predict patenting in the same way that past funding changes do. In fact, the opposite is the case, reflecting mean reversion after funding shocks. Note that mean reversion at the aggregate CFDA-year level does not imply that a researcher can easily return to her previous funding mix, because federal grants have lead times of typically more than a year, and the average grant lasts for several years. Second, if funding changes are predictable, we expect that they will exhibit long term incremental trends. This is not the case because unlike lagged changes, future changes do not positively predict the federal share. We also show that the results are robust to using only large year-to-year funding shocks. Third, there may be concern that loss of federal funding is negative career shock even if that funding is replaced with private funding, and despite controlling for the individual's expenditure. However, a higher federal share leads to lower 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.

The main takeaway from our results is 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.

Why are different funding sources more effective at producing different research outputs? One lens through which to view these results is the spectrum from basic to applied (i.e. more downstream or near-commercial) research. Many of the results are supportive of federal funds leading to more basic research, and private funds leading to more applied research. For instance, a higher share of federal funding leads to fewer, but more general patents. However, it seems likely that more applied research would also yield more startups, yet federal funding causes much more high-tech entrepreneurship.

Thus, our results may best be viewed through a different lens – the spectrum from more to less appropriable research. 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. Aghion et al. (2008) provide one mechanism; private 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 particular to the funder. 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). Federal funding likely has fewer strings attached, so the intellectual property is freer to be used in 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.

In sum, our findings indicate that a key difference between federal and private funding lies in contractual arrangements for how intellectual property is commercialized. We can view this as reflecting different constraints on the two types of funding. Private research appears to have the constraint that it is more applied and more appropriable. Being more applied predicts both more startups and more patents, while being more appropriable predicts more patents but fewer startups. Our evidence is consistent with the latter, suggesting that the appropriability constraint binds on the set of individuals who are at hazard of either type of funding, and thus comprise the compliers with the instrument.

Our paper builds on a rich literature about innovation investment and the knowledge spillovers it generates. Research in this area has focused on private firm innovation (e.g., Bernstein and Nadiri 1989, Bloom et al. 2013), leaving the impact of public sector research investments relatively unexplored. This paper contributes to the debate on real effects of public research funding. On the one hand, seminal paper by Goolsbee (1998) argues that government efforts to increase inventive activity face a serious problem: since majority of R&D spending is salary on R&D workers and their labor supply is inelastic, a significant fraction of government funding goes into higher wages. On the other hand, Azoulay et al. (2019) document the impact of public funding on private innovation in the biotech industry. 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 university funding sources on the creation of new businesses, contributing to the literature on how universities affect innovation (Shane and Stuart, 2002; Lach and Schankerman, 2008; Hegde, 2009; Belenzon and Schankerman, 2009, 2013; Guerzoni et al., 2017; Li et al., 2017; Tartari and Stern, 2018; Tabakovic and Wollmann, 2019; Watzinger and Schnitzer, 2019).

The key contribution of this paper is to establish the effects of the source of university research funds on innovation and labor mobility—the key channels of knowledge diffusion. Our finding that private funding leads to less general patents is related to work finding declines in the quality of

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

university patents (Henderson et al. 1998). While several explanations has been put forth, one of the key mechanisms is may be the aggregate shift from public to privately-funded research (Foray and Lissoni 2010). Indeed, while public funding may target research areas with the most potential for follow-on innovation (Acemoglu and Linn 2004), private innovation appropriated though patents can discourage follow on innovation by either public or private parties (Galasso and Schankerman 2015).

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

[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.

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). 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

[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).

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 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 4.6).

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 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 4.6 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).

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

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, undergraduate student, and other) and department (e.g. physics, biology, etc). 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 (including post-docs), 38% are staff members, and 13% are undergraduate students.[10] More than 20% of the researchers have received funding from both federal

[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.

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 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.

[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.

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 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 are reported to the IRS by individuals' employers and are required in industries and for workers who are not covered by unemployment insurance. The W-2 records report annual wages for all workers with tax-withholdings in the U.S, with complete coverage for all states from 2005 to 2017. 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

[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 the United States and contains information on each establishment's employment, payroll, industry (NAICS code), EIN, and a firm identifier developed by the Census Bureau (DeSalvo et al., 2016). The LBD links establishments in the BR over time, which allows us to obtain the age of each firm (Jarmin and Miranda, 2002). The LEHD ECF is the universe of establishments that report earnings to state unemployment insurance agencies, and contains information on employment, payroll, industry, and the Census-developed firm identifier (McKinney and Vilhuber, 2011). IPEDS is a database maintained by the National Center for Education Statistics (NCES), and provides a wide variety of information on colleges, universities, and technical and vocational schools in the United States. 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.[15] 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.[16] High-tech NAICS are defined according to the NSF classification.[17] These datasets are combined to create a complete job history panel. If a PIK-year exists in the LEHD with a linked EIN or Census firm identifier, we use this observation of employment. We then add all PIK-years found in the W-2 records that do not overlap with the LEHD data (i.e., no PIK-year should have information from both the LEHD and W-2s). 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 outcome variables, which characterize the entrepreneurial and employment activity of each person-year: 1) an indicator for

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

[16] 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.

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

whether the individual works at a firm aged zero this year or in the next two years (*entrepreneurship*), 2) 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*), 3) an indicator for whether the individual works at an age-five or older firm this year or in the next two years (*incumbent employment*), and 4) an indicator for whether the individual works at a university this year or in the next two years (*university employment*). We define an individual's wage using their dominant job – that is the job from which they are paid the most.[18]

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 $\text{R\&D}_{i,t-1}$ 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 $\text{R\&D}_{i,t-2}$ 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.

The instrument also negatively affects share of funding from industry funders and other sources. A one-standard-deviation increase in $\text{R\&D}_{i,t-2}$ 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.

[18] We also impute the wages of very low earning and high earning individuals.

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 3-6. 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.

We examine whether a particular type of researcher is responsible for the effects by splitting the sample according to the occupation classes 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 0.047, significant at the .01 level, means that a 10% increase in the mean of the federal share increases the probability of high-tech entrepreneurship by 60% of the mean, which is 0.6%. This is not the case for entrepreneurship in general, which predominantly consists from low-tech and low-growth entrepreneurship, where the coefficient is near zero relative to the mean (column 2).

We find that an increased federal funding share 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 3), and increases the probability that they work for a university (column 4). Note that these do not measure the same object, 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 4% (3%) of the mean. We find similar results when we restrict the sample to high-tech incumbent firms.

The final column in Table 6 shows that a higher federal share of funding leads to a significantly lower wage in year t. In a robustness test below, this relationship switches sign without the expenditure control. Since researchers' salaries are often paid out of grants, and federal grants are typically larger than private grants, without the expenditure control there is a positive relationship. The negative effect with the control may reflect researchers doing more consulting work for private firms when they receive private grant funding. If private funders more tightly control the direction of research, as stipulated in Aghion et al. (2008), this result is consistent with the prediction that researchers demand a wage premium in exchange for giving up control rights, a prediction founded in the property rights literature (Hart and Moore 1990**,** Aghion and Tirole 1997**).** Also related, Stern (2004) finds that recent biology PhD's accept significantly lower wages at jobs where they are encouraged to publish or have greater research freedom.

We next describe how these career outcomes vary by researcher occupation. (These results are not yet reported, as they involve complex disclosure processes, but will be in future drafts.) The large positive effect on high-tech entrepreneurship is driven by graduate and undergraduate students, with faculty having a similar magnitude but without significance. There is a fairly precise zero effect for staff. The negative effect on working at an incumbent firm is driven by undergraduates; there is

no effect among faculty. Among graduate students, the coefficient is negative but insignificant. The negative effect on working at a university is driven by undergraduates and graduates. Even with the smaller samples, the F-statistics for all of these results are well above the rule of thumb cutoff of 10.

4.4 Private Share

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 7 and 8, 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 7 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 8. A 10% increase in the mean of the private share reduces the chances of becoming a high-tech entrepreneur by 13% of

the mean. The relationship between the share of private funding and working for an incumbent firm is statistically insignificant and close to zero, and so it is not simply the reverse of the (negative) effect of the federal share. As noted, the negative effect of the federal share is driven by undergraduate students and, indeed, the effect of the private share on undergraduates is positive and statistically significant (not reported). However, the effects of both the federal and private shares are negative for graduate students, who account for a large fraction of the observations. These negative effects reinforce the negative effects of the federal share on undergraduates (leading to an overall negative effect) and counteract the positive effects of the private share (leading to an overall zero effect). Note that negative effects for both the federal and private shares are possible when the effects of the residual share (i.e. 1 minus the federal plus private shares) are positive, which they are for graduate students. We find a robust negative effect of the private share on working at a university (column 4), and a positive effect on the wage (column 5). In sum, with the exception of working at an incumbent firm, the results are inverted and larger in magnitude when we consider private funding.

4.5 Naive Relationship

In this section, 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.1. 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 naive 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.2, the OLS relationships are quite different. 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, are somewhat more likely to work for incumbents, and are slightly less likely to work for a university (Appendix Table A.2 columns 1-3). When split by occupation, the latter two results are driven by other staff (not reported).

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. Also, more elite faculty who select into federal funding may be less likely to leave for high-tech entrepreneurship if their university job is more satisfactory. Note that they may nonetheless have significant equity stakes in startups that use technology from their labs, which we do not observe. In other words, compliers with the instrument are are more likely to be on margin for entering high-tech entrepreneurship.

4.6 Robustness Tests

This section addresses a number of potential concerns with the main analysis. Most are provided only for the patent analysis, but will be disclosed for the career outcomes from Census data in future drafts.

A central concern is that the results reflect not the funding source itself, but one of two alternative mechanisms that may be correlated with changes to government funding: technological opportunities in the sector, or downstream federal incentives. 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 better test is as follows. If either technological opportunities or downstream policies explain the effects, then researchers in the same CFDA code that are not compliers with the instrument should also respond to the funding changes. In Appendix Table A.3 columns 7-8 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 very unlikely. At a minimum, we would expect to see attenuated results, but instead, we find null effects.

If technological opportunities explain both the federal funding changes and the innovation outcomes, future funding changes should have predictive power over patenting that is similar to past funding changes (which are the instrument). To explain further, recall that the main result finds that a higher federal share reduces patenting. If this were driven by technological opportunities, future federal funding changes in the CFDA code should also negatively predict patenting. However, Appendix Table A.3 columns 1-4 show the opposite: while past changes negatively predict patenting, consistent with the instrumented result (columns 1-2), there is a positive relationship between future changes and patenting activity (columns 3-4). This positive relationship reflects the tendency towards mean reversion after shocks to federal funding, but no such mean reversion in future patenting. Note that mean reversion at the aggregate CFDA-year level does not mean it is straightforward for a researcher to return to her previous funding mix. Academics typically face long grant application lead times, and do not win and use only new grants each year. Instead, a grant typically takes at least a year to win and lasts for several years.

A related concern may be that the results are driven by long term trends in funding rather than

one-time, idiosyncratic changes. However, only past changes in federal funding positively predict the federal share. If the results were driven by government spending trends that are predictable, we would expect future changes to also have predictive power over the federal share. Instead, we find the opposite, again because most of the variation in our data come from shocks that mean revert. Appendix Table A.3 columns 5-6 show that there is a negative relationship between future changes in funding and the current federal share. In a second test, we restrict changes in CFDA-level expenditure to large funding shocks, where year to year funding increased or decreased by more than 30% in a single CFDA code. The results, in Appendix Table A.4, are very similar to the main findings, but slightly larger in magnitude. This offers strong evidence that it would be impossible to predict funding and that the results do not reflect medium or long term trends in federal spending.

The next robustness test omits the control for expenditure, in case that is somehow biasing the effects. The results, in Appendix Table A.5, are similar, but less robust for some outcomes such as having any patents, and larger and more robust for others, such as having any general patents. This seems likely related to the strong correlation between expenditure and patenting. Appendix Table A.6 does the same, but for the career outcomes. Here the results are very similar, except that the effect on wage becomes positive and insignificant, whereas in the main results it is negative and robust. As mentioned above, this likely reflects the fact that researchers' salaries are often paid out of grants, and federal grants are typically larger than private grants, so without the control for expenditure, there is a positive relationship.

Another concern related to expenditure is that loss of federal funding might be a negative career shock even if that funding is replaced with private funding, and despite controlling for the individual's total expenditure. However, a higher federal share leads to lower wages in the IV (and somewhat higher wages in OLS), 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. The final robustness test uses an alternative assumption for clustering standard errors. Instead of at the individual level, we cluster at the university-by-field level. The results

for patenting, shown in Appendix Table A.7 remain robust, though the effect on generality becomes insignificant, albeit barely so.

5 Discussion

The results help to shed light on common perceptions about the role of federal funding in university research, and the tradeoffs between federal and industry sources. 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," 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, as some observers argue that federal funders have shifted post-2000 towards demanding more applied work and immediately commercially useful research outputs.[19] Another factor is the greater focus on commercialization at the university level. Following the Bayh-Dole Act of 1980, it has been 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, but not more citations. Conditional on patenting,

[19] 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.

federal funding is associated with more citations per patent. Similarly, the lower rate of joining an incumbent firm from federal funding is consistent with more applied work. 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. 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, it is not obvious why such ideas would be earlier stage. Therefore, it is most intuitive to assume that more applied research will yield more startups, making it a bit surprising that federal funding leads to such a higher rate of high-tech entrepreneurship.

A third dimension is the degree to which research outputs are privately appropriable, and who is able to appropriate 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, however, gives rise to more general patents, indicating that these outputs are more accessible to a broader range of future researchers.

Second, private funding leads to a dramatically lower rate of high-tech entrepreneurship, consistent with the funder appropriating research outputs and preventing them from being used by grant employees in startups. The idea here is that federal funding has fewer strings attached, so the intellectual property is freer to be used in a startup. The result complements Hvide and Jones (2018), who find a negative effect on faculty entrepreneurship when invention rights were reallocated from the professor to the university. If the same mechanism were at play in our context, the negative effect of

private funding on startups would suggest that private funding reallocates rights from faculty and students to the funder. However, Hvide and Jones (2018) find that reducing professors' rights to their inventions also reduces patent activity. We find that private funding increases patent activity. This suggests that the mechanism in our context is not simply about whether the professor owns the invention or not, but whether the funder owns the invention and chooses to appropriate it. That is, privately funded research outputs are more often appropriated by the private sector through patents, while federally funded research outputs are more open, less likely to be patented, and more often are spun out into startups. It is important to stress, however, that consistency with an appropriability hypothesis by no means rules out other channels.

The greater appropriability of university research after the Bayh-Dole Act of 1980 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 in different directions, and in particular 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.

In sum, our research shows that federal and private funding for university research are not perfect substitutes. Further, the results indicate that private funds lead to intellectual property that is more often appropriated through patents, and less often deployed in startups. This suggests that a key difference between federal and private funding lies in contractual arrangements for how intellectual property is

commercialized. We can view this as reflecting different constraints. Private research appears to have the constraint that it is more applied and appropriable. Being applied predicts both more startups and more patents, while being appropriable predicts more patents but fewer startups. Our evidence is consistent with the latter, suggesting that the appropriability constraint binds on the set of individuals who are at hazard of either type of funding (and thus will comply with our instrument).

The policy implications of these findings are complex and beyond the scope of our work. However, it is worth outlining several factors that are relevant for policy. One factor is that universities are increasingly dependent on industry funding, and many actively recruit corporate research sponsors. 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."[20] 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.

A second factor is that federal funding may crowd 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.

Third, while our analysis points to larger knowledge spillovers from federal funding, there are important caveats to this conclusion. We find that federal funding leads to more basic, open research, while privately funded research appears to be more immediately appropriated by incumbent firms. However, we cannot evaluate the magnitude of knowledge 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

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

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. 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.

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.

References

Acemoglu, Daron and Joshua Linn, "Market size in innovation: theory and evidence from the pharmaceutical industry," *The Quarterly journal of economics*, 2004, *119* (3), 1049–1090.

Aghion, Philippe and Jean Tirole, "Formal and real authority in organizations," *Journal of political economy*, 1997, *105* (1), 1–29.

_ , Mathias Dewatripont, and Jeremy C Stein, "Academic freedom, private-sector focus, and the process of innovation," *The RAND Journal of Economics*, 2008, *39* (3), 617–635.

Arrow, Kenneth, "Economic welfare and the allocation of resources for invention. The rate and direction of inventive activity: economic and social factors," *N. Bureau*, 1962.

Åstebro, Thomas, Navid Bazzazian, and Serguey Braguinsky, "Startups by recent university graduates and their faculty: Implications for university entrepreneurship policy," *Research policy*, 2012, *41* (4), 663–677.

Astebro, Tom and Navid Bazzazian, "Universities, entrepreneurship and local economic development," *Handbook of Research on Entrepreneurship and Regional Development: National and Regional Perspectives*, 2011, pp. 252–333.

Audretsch, David B and Maryann P Feldman, "R&D spillovers and the geography of innovation and production," *The American economic review*, 1996, *86* (3), 630–640.

Autor, David, David Dorn, and Gordon Hanson, "The China syndrome: local labor market effects of import competition in the United States," *American Economic Review*, 2013, *103* (6), 2121–68.

Avnimelech, Gil and Maryann P Feldman, "The stickiness of university spin–offs: A study of formal and informal spin–offs and their location from 124 US academic institutions," *International Journal of Technology Management*, 2015, *68* (1-2), 122–149.

Azoulay, Pierre, Joshua S Graff Zivin, and Gustavo Manso, "Incentives and creativity: evidence from the academic life sciences," *The RAND Journal of Economics*, 2011, *42* (3), 527–554.

_ , _ , Danielle Li, and Bhaven N Sampat, "Public R&D investments and private-sector patenting: evidence from NIH funding rules," *The Review of economic studies*, 2019, *86* (1), 117–152.

Babina, Tania and Sabrina T Howell, "Entrepreneurial spillovers from corporate R&D," Technical Report, National Bureau of Economic Research 2019.

_ , Asaf Bernstein, and Filippo Mezzanotti, "Crisis Innovation," 2019.

Balsmeier, Benjamin, Maria Kurakina, and Lee Fleming, "R&D tax credits: Mechanisms of private and public value," *Berkeley, CA: Haas Business School*, 2018.

Belenzon, Sharon and Mark Schankerman, "University knowledge transfer: private ownership, incentives, and local development objectives," *The Journal of Law and Economics*, 2009, *52* (1), 111–144.

_ and _ , "Spreading the word: Geography, policy, and knowledge spillovers," *Review of Economics and Statistics*, 2013, *95* (3), 884–903.

Bernstein, Jeffrey I and M Ishaq Nadiri, "Research and development and intra-industry spillovers: an empirical application of dynamic duality," *The Review of Economic Studies*, 1989, *56* (2), 249–267.

Bloom, Nicholas, Mark Schankerman, and John Van Reenen, "Identifying technology spillovers and product market rivalry," *Econometrica*, 2013, *81* (4), 1347–1393.

Bloom, Nick, Rachel Griffith, and John Van Reenen, "Do R&D tax credits work? Evidence from a panel of countries 1979–1997," *Journal of Public Economics*, 2002, *85* (1), 1–31.

Budish, Eric, Benjamin N Roin, and Heidi Williams, "Do firms underinvest in long-term research? Evidence from cancer clinical trials," *American Economic Review*, 2015, *105* (7), 2044–85.

Dechezleprêtre, Antoine, Elias Einiö, Ralf Martin, Kieu-Trang Nguyen, and John Van Reenen, "Do tax incentives for research increase firm innovation? An RD design for R&D," Technical Report, National Bureau of Economic Research 2016.

Decker, Ryan, John Haltiwanger, Ron Jarmin, and Javier Miranda, "The role of entrepreneurship in US job creation and economic dynamism," *Journal of Economic Perspectives*, 2014, *28* (3), 3–24.

DeSalvo, Bethany, Frank Limehouse, and Shawn D Klimek, "Documenting the Business Register and Related Economic Business Data," *US Census Bureau Center for Economic Studies Paper No. CES-WP-16-17*, 2016.

Djokovic, Djordje and Vangelis Souitaris, "Spinouts from academic institutions: a literature review with suggestions for further research," *The journal of technology transfer*, 2008, *33* (3), 225–247.

Drazen, Jeffrey, "The quality of medical Research, not Its Source of Funding, Is What Matters," *The New York Times*, Sep 2016.

Feldman, Maryann, Irwin Feller, Janet Bercovitz, and Richard Burton, "Equity and the technology transfer strategies of American research universities," *Management Science*, 2002, *48* (1), 105–121.

Foray, Dominique and Francesco Lissoni, "University research and public–private interaction," in "Handbook of the Economics of Innovation," Vol. 1, Elsevier, 2010, pp. 275–314.

Galasso, Alberto and Mark Schankerman, "Patents and cumulative innovation: Causal evidence from the courts," *The Quarterly Journal of Economics*, 2015, *130* (1), 317–369.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift, "Bartik Instruments: What, When, Why, and How," *American Economic Review*, 2019, *Forthcoming*.

Goolsbee, Austan, "Does government R&D policy mainly benefit scientists and engineers?," Technical Report, National bureau of economic research 1998.

Guerzoni, Marco, T Taylor Aldridge, David B Audretsch, and Sameeksha Desai, "A new industry creation and originality: Insight from the funding sources of university patents," in "Universities and the Entrepreneurial Ecosystem," Edward Elgar Publishing, 2017.

Hall, Bronwyn and John Van Reenen, "How effective are fiscal incentives for R&D? A review of the evidence," *Research policy*, 2000, *29* (4-5), 449–469.

Hart, Oliver and John Moore, "Property Rights and the Nature of the Firm," *Journal of political economy*, 1990, *98* (6), 1119–1158.

Hausman, Naomi, "University innovation and local economic growth," *Maurice Falk Institute for Economic Research in Israel. Discussion paper series.*, 2017, (5), 0_1–63.

Hegde, Deepak, "Political influence behind the veil of peer review: An analysis of public biomedical research funding in the United States," *The Journal of Law and Economics*, 2009, *52* (4), 665–690.

Henderson, Rebecca, Adam B Jaffe, and Manuel Trajtenberg, "Universities as a source of commercial technology: a detailed analysis of university patenting, 1965–1988," *Review of Economics and statistics*, 1998, *80* (1), 119–127.

Howell, Sabrina T, "Financing innovation: Evidence from R&D grants," *American Economic Review*, 2017, *107* (4), 1136–64.

Hvide, Hans K and Benjamin F Jones, "University innovation and the professor's privilege," *American Economic Review*, 2018, *108* (7), 1860–98.

Jacob, Brian A and Lars Lefgren, "The impact of research grant funding on scientific productivity," *Journal of public economics*, 2011, *95* (9-10), 1168–1177.

Jaffe, Adam B, "Real effects of academic research," *The American economic review*, 1989, pp. 957–970.

Jarmin, Ron S and Javier Miranda, "The longitudinal business database," *Available at SSRN 2128793*, 2002.

Kline, Patrick, Neviana Petkova, Heidi Williams, and Owen Zidar, "Who profits from patents? rent-sharing at innovative firms," *The Quarterly Journal of Economics*, 2019, *134* (3), 1343–1404.

Lach, Saul and Mark Schankerman, "Incentives and invention in universities," *The RAND Journal of Economics*, 2008, *39* (2), 403–433.

Li, Danielle, Pierre Azoulay, and Bhaven N Sampat, "The applied value of public investments in biomedical research," *Science*, 2017, *356* (6333), 78–81.

Markoff, John, "Pentagon redirects its research dollars," *Pp. C-1 in The New York Times. New York, April*, 2005, *2*.

McCluskey, Molly, "Public Universities Get an Education in Private Industry," *The Atlantic*, 2017, *3*.

McKinney, Kevin L and Lars Vilhuber, "LEHD infrastructure files in the census RDC: Overview of S2004 snapshot," *US Census Bureau Center for Economic Studies Paper No. CES-WP-11-13*, 2011.

Mervis, Jeffrey, "Data check: US government share of basic research funding falls below 50%," *Science*, 2017, *10*.

Moretti, Enrico, Claudia Steinwender, and John Van Reenen, "The Intellectual Spoils of War? Defense R&D, Productivity and International Spillovers," Technical Report, National Bureau of Economic Research 2019.

Mowery, David C, Bhaven N Sampat, and Arvids A Ziedonis, "Learning to patent: Institutional experience, learning, and the characteristics of US university patents after the Bayh-Dole Act, 1981-1992," *Management Science*, 2002, *48* (1), 73–89.

Myers, Kyle, "The elasticity of science," *Available at SSRN 3176991*, 2019.

NAP, *Intellectual Property Rights in Industry-Sponsored University Research: A Guide to Alternatives for Research Agreements*, Washington, DC: The National Academies Press, 1993.

Nelson, Richard R, "The simple economics of basic scientific research," *Journal of political economy*, 1959, *67* (3), 297–306.

O'shea, Rory P, Thomas J Allen, Arnaud Chevalier, and Frank Roche, "Entrepreneurial orientation, technology transfer and spinoff performance of US universities," *Research policy*, 2005, *34* (7), 994–1009.

Robinson, David T, "Strategic alliances and the boundaries of the firm," *The Review of Financial Studies*, 2008, *21* (2), 649–681.

Rothaermel, Frank T, Shanti D Agung, and Lin Jiang, "University entrepreneurship: a taxonomy of the literature," *Industrial and corporate change*, 2007, *16* (4), 691–791.

Shane, Scott and Toby Stuart, "Organizational endowments and the performance of university start-ups," *Management science*, 2002, *48* (1), 154–170.

Siegel, Donald S, Mike Wright, and Andy Lockett, "The rise of entrepreneurial activity at universities: organizational and societal implications," *Industrial and Corporate Change*, 2007, *16* (4), 489–504.

Stern, Scott, "Do scientists pay to be scientists?," *Management science*, 2004, *50* (6), 835–853.

Tabakovic, Haris and Thomas G Wollmann, "The impact of money on science: Evidence from unexpected NCAA football outcomes," *Journal of Public Economics*, 2019, *178*, 104066.

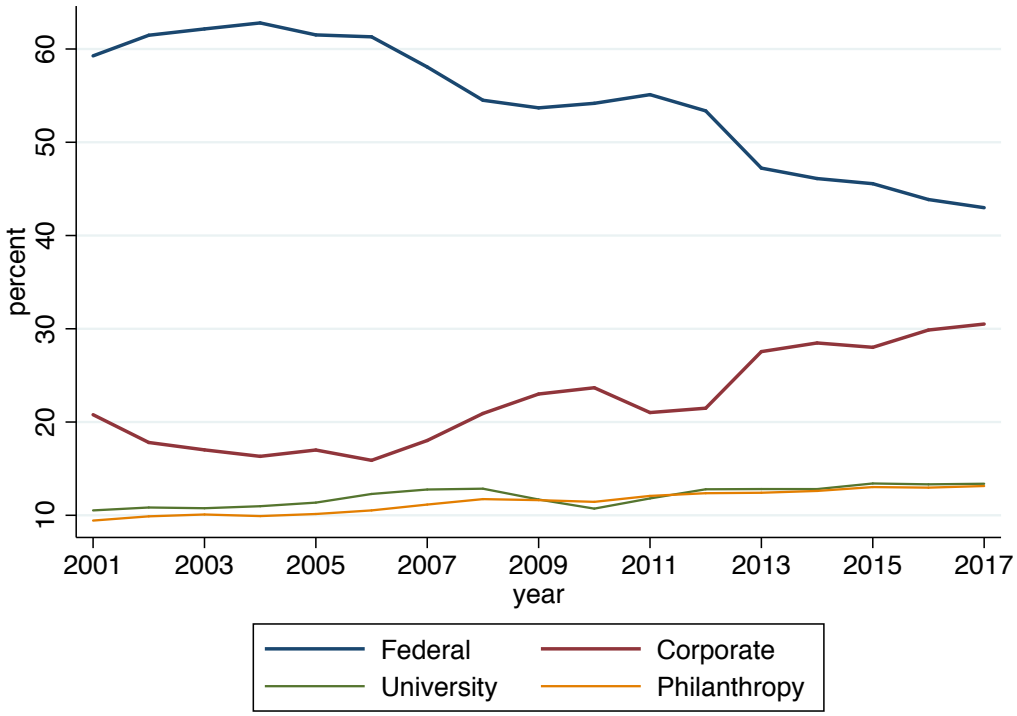
Tartari, Valentina and Scott Stern, "The Role of Universities in Local Entrepreneurial Ecosystems," 2018.

Trajtenberg, Manuel, Rebecca Henderson, and Adam Jaffe, "University versus corporate patents: A window on the basicness of invention," *Economics of Innovation and new technology*, 1997, *5* (1), 19–50.

Watzinger, Martin and Monika Schnitzer, "Standing on the Shoulders of Science," 2019.

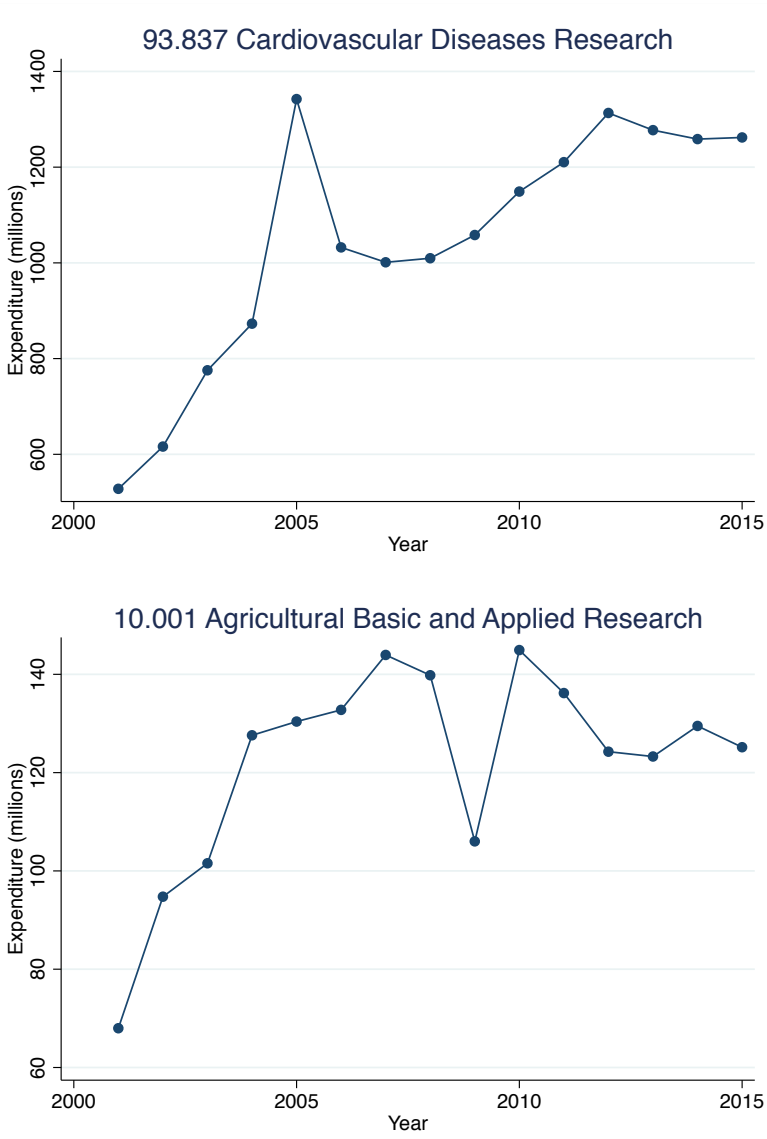
Zucker, Lynne G, Michael R Darby, and Marilynn B Brewer, "Intellectual human capital and the birth of US biotechnology enterprises.," *American Economics Review*, 1998, *88*, 8.

Figure 1. Sources of U.S. Research Funding, 2001-2017



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 2001 to 2017. 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.

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. 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	1	0.345
Share Private$_{i,t-1}$	571,000	0.111	0	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	Median	Standard Deviation
Panel C: Census				
Number of Unique Piks	146,000			
High-tech Entrepreneur$_{i,[t,t+2]}$	444,000	0.0063		
Entrepreneur$_{i,[t,t+2]}$	444,000	0.0234		
Work for Incumbent Firm$_{i,[t,t+2]}$	444,000	0.353		
Work for University$_{i,[t,t+2]}$	444,000	0.833		
Real Wage$_{i,t}$	444,000	51,000	33,000	55,000
Number of Jobs$_{i,t}$	444,000	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 weighted average of funding changes in CFDA programs as described in Section 2. The baseline sample is a person-year panel from 2001 through 2015 (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. 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×Year×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. 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 × Year × 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. 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). 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. 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$_{i,[t,t+2]}$	Entrepreneur$_{i,[t,t+2]}$	Work for Incumbent Firm$_{i,[t,t+2]}$	Work for University$_{i,[t,t+2]}$	Log(Wage$_{i,t}$)
	(1)	(2)	(3)	(4)	(5)
Share Federal$_{i,t-1}$	0.0472***	-0.0046	-0.1690**	0.2969***	-0.9563***
	(0.0123)	(0.0231)	(0.0675)	(0.0557)	(0.1542)
Log(Expenditure$_{i,t-1}$)	0.0001	-0.0052***	-0.0740***	0.0566***	0.1599***
	(0.0001)	(0.0002)	(0.0007)	(0.0006)	(0.0017)
University×Year×Field FE	Yes	Yes	Yes	Yes	Yes
Number of Observations	444,000	444,000	444,000	444,000	444,000
Mean of Dependent Variable	0.0063	0.0234	0.353	0.833	51,000
F-statistic	151	151	151	151	151

Table 7. 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×Year×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 8. 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). 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. 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$_{i,[t,t+2]}$	Entrepreneur$_{i,[t,t+2]}$	Work for Incumbent Firm$_{i,[t,t+2]}$	Work for University$_{i,[t,t+2]}$	Log(Wage$_{i,t}$)
	(1)	(2)	(3)	(4)	(5)
Share Private$_{i,t-1}$	-0.0717***	-0.0055	0.0034	-0.3019***	1.454***
	(0.0183)	(0.0339)	(0.0981)	(0.0811)	(0.2340)
Log(Expenditure$_{i,t-1}$)	-0.0000	-0.0052***	-0.0728***	0.0554***	0.1620***
	(0.0001)	(0.0002)	(0.0006)	(0.0005)	(0.0015)
University×Year×Field FE	Yes	Yes	Yes	Yes	Yes
Number of Observations	444,000	444,000	444,000	444,000	444,000
Mean of Dependent Variable	0.0063	0.0234	0.353	0.833	51,000
F-statistic	91	91	91	91	91

A Appendix

Table A.1. OLS Effect of the Share of Federal Funding on Patent Outcomes

Table reports second stage results of the 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.2. OLS Effect of the Share of Federal Funding on Career Outcomes

Table reports second stage results of the 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). 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. 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$_{i,[t,t+2]}$	Log(Wage$_{i,t}$)
	(1)	(2)	(3)	(4)
Share Federal$_{i,t-1}$	-0.0003	0.0529***	-0.0420***	-0.0768***
	(0.0005)	(0.0032)	(0.0021)	(0.0071)
Log(Expenditure$_{i,t-1}$)	-0.0002	-0.0620***	0.0482***	0.1386***
	(0.0001)	(0.0008)	(0.0006)	(0.0018)
University×Year×Field FE	Yes	Yes	Yes	Yes
Number of Observations	444,000	444,000	444,000	444,000
Mean of Dependent Variable	0.0063	0.353	0.833	51,000

Table A.3. Robustness. IV Effect of the Share of Federal Funding on Patent Outcomes: Placebo Effect for Non-switchers and Future Funding Changes

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.

	Reduced Form				IV First-Stage		Non-Switchers	
	Any Patents$_{i,t}$	Number of Patents$_{i,t}$	Any Patents$_{i,t}$	Number of Patents$_{i,t}$	Share Federal$_{i,t}$	Share Private$_{i,t}$	Any Patents$_{i,t}$	Number of Patents$_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log-change Amount R&D$_{i,t-1}$	-0.0002***	-0.0004***					-0.0001	-0.0001
	(0.0001)	(0.0001)					(0.0001)	(0.0001)
Log-change Amount R&D$_{i,t-2}$	-0.0002***	-0.0003***					-0.0001	-0.0001
	(0.0001)	(0.0001)					(0.0001)	(0.0001)
Log-change Amount R&D$_{i,t+1}$			0.0003***	0.0005***	-0.0020***	0.0012***		
			(0.0001)	(0.0001)	(0.0002)	(0.0002)		
Log-change Amount R&D$_{i,t+2}$			0.0002***	0.0003***	-0.0027***	0.0017***		
			(0.0000)	(0.0001)	(0.0004)	(0.0003)		
Log(Expenditure$_{i,t-1}$)	0.0031***	0.0046***	0.0036***	0.0055***	0.0067***	0.0038***	0.0011***	0.0013***
	(0.0001)	(0.0003)	(0.0002)	(0.0004)	(0.0005)	(0.0004)	(0.0001)	(0.0001)
University×Year×Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	571,000	571,000	474,000	474,000	570,000	570,000	282,000	282,000
Adjusted R-squared	0.014	0.012	0.013	0.011	0.157	0.101	0.007	0.006

Table A.4. Robustness. IV Effect of the Share of Federal Funding on Patent Outcomes: Using Large Federal Funding Shocks

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.

Panel A

	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$_{i,t-1}$	-0.0519***	-0.0810***	-0.0008	-0.0171*	0.0114*	-0.0090***
	(0.0144)	(0.0205)	(0.0048)	(0.0097)	(0.0061)	(0.0029)
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 × Year × Field FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	571,000	571,000	571,000	571,000	571,000	571,000
F-statistic	111	111	111	111	111	111

Panel B

	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$_{i,t-1}$	0.0747***	0.1163***	0.0013	0.0240*	-0.0167*	0.0128***
	(0.0209)	(0.0299)	(0.0070)	(0.0140)	(0.0089)	(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 × Year × Field FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	571,000	571,000	571,000	571,000	571,000	571,000
F-statistic	92.3	92.3	92.3	92.3	92.3	92.3

Table A.5. IV Effect of the Share of Federal Funding on Patent Outcomes without Expenditure Control
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.

Panel A

	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$_{i,t-1}$	-0.0207	-0.0347*	0.0019	-0.0038	0.0151***	-0.0068***
	(0.0128)	(0.0179)	(0.0044)	(0.0088)	(0.0057)	(0.0025)
University×Year×Field FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	571,000	571,000	571,000	571,000	571,000	571,000
F-statistic	131	131	131	131	131	131

Panel B

	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$_{i,t-1}$	0.0345	0.0570*	-0.0026	0.0052	-0.0253***	0.0111***
	(0.0211)	(0.0298)	(0.0074)	(0.0145)	(0.0094)	(0.0042)
University×Year×Field FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	571,000	571,000	571,000	571,000	571,000	571,000
F-statistic	84.5	84.5	84.5	84.5	84.5	84.5

Table A.6. IV Effect of the Share of Federal Funding on Career Outcomes without Expenditure Control
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$_{i,[t,t+2]}$		Log(Wage$_{i,t}$)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share Federal$_{i,t-1}$	0.0476***		-0.6485***		0.6643***		0.0856	
	(0.0129)		(0.0796)		(0.0670)		(0.1596)	
Share Private$_{i,t-1}$		-0.0713***		0.6423***		-0.7904***		0.0047
		(0.0188)		(0.1123)		(0.0976)		(0.2304)
University×Year×Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	444,000	444,000	444,000	444,000	444,000	444,000	444,000	444,000
Mean of Dependent Variable	0.0063	0.0063	0.353	0.353	0.833	0.833	51,000	51,000
F-statistic	137	85	137	85	136	85	137	85

Table A.7. Robustness. IV Effect of the Share of Federal Funding on Patent Outcomes: Cluster Standard Errors at University-By-Field Level

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.

Panel A

	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*
	(0.0258)	(0.0370)	(0.0034)	(0.0127)	(0.0079)	(0.0049)
Log(Expenditure$_{i,t}$)	0.0034***	0.0051***	0.0004***	0.0015***	0.0005**	0.0002
	(0.0008)	(0.0013)	(0.0001)	(0.0003)	(0.0002)	(0.0001)
University×Year×Field FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	571,000	571,000	571,000	571,000	571,000	571,000
F-statistic	26.28	26.28	26.28	26.28	26.28	26.28

Panel B

	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*
	(0.0371)	(0.0531)	(0.0050)	(0.0186)	(0.0121)	(0.0072)
Log(Expenditure$_{i,t}$)	0.0028***	0.0041***	0.0004***	0.0013***	0.0006***	0.0001*
	(0.0007)	(0.0011)	(0.0001)	(0.0003)	(0.0002)	(0.0001)
University×Year×Field FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	571,000	571,000	571,000	571,000	571,000	571,000
F-statistic	10.81	10.81	10.81	10.81	10.81	10.81