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The impact of money on science: Evidence from unexpected NCAA football outcomes[☆]

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ABSTRACT

How productive are university research investments, and do the resulting pools of knowledge create valuable, downstream technology — or simply accumulate in the "ivory tower"? This paper uses unexpected NCAA athletic outcomes to vary research support to university faculty and estimate knowledge productivity. We find positive, significant effects of research expenditures on articles published and patents filed. Then, using data on university technology licensing income, we show that these investments produce large returns in real terms.

1. Introduction

Scientific discovery drives economic growth, so determining the optimal level of R&D is a main goal of many policymakers and administrators. In developed economies, two broad, secular trends are changing the parameters governing this problem. The first is a shift to university-led R&D.[1] The second is increasing reliance on internal rather than government funding sources.[2] This issue is particularly salient in the US, where the share of internally funded university R&D has nearly doubled over the last four decades. The policy debate has been contentious. In 2007, US Congress passed the American COMPETES Act—legislation intended to double the level of funding to certain STEM[3] fields—but austerity measures delayed and reduced the scope of the original legislation. Recently, deep cuts were proposed by the President's 2019 budget, though these were ignored by Congress. Advocates for R&D funding emphasize path-breaking innovations generated by university research. The director of the National Institute of Health stated, for example, that without added support,

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1 OECD. OECD Reviews of Innovation Policy-Sweden. Organisation for Economic Co-operation and Development, 2013.
2 OECD. OECD Science, Technology and Industry Outlook. Organisation for Economic Co-operation and Development, 2014.
3 "STEM" is the commonly-used acronym for "natural science, technology, engineering, and mathematics."

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"a lot of good science just won't be done."[4] Critics, on the other hand, cite allegedly unproductive spending at the margin.

This paper addresses two questions at the core of the issue. First, how large of an impact do institutionally funded university research expenditures have on scientific productivity? There is scarce work on the university's knowledge production function, even though understanding it is crucial to informing a policy debate that stretches back at least to works by Nelson (1959) and Arrow (1962).[5] Moreover, there is little work specific to institutionally funded research, which is increasingly relied on but can differ from other funding sources in important ways.[6] Second, does the pool of knowledge derived from academic research create valuable downstream technology at the intensive margin or simply accumulate inside the "ivory tower"? This transport of ideas is at the core of the economics of innovation and technology, crucial to endogenous growth (Romer, 1990), and of the motivation for a large literature studying "real effects" of university research, starting with influential work by Jaffe (1989). This literature provides strong evidence of spillovers from academic activity to private sector outcomes but ultimately does not *per se* provide proof that marginal university R&D expenditures generate valuable downstream technology. For example, while university R&D spending increases the local pool of knowledge, it also increases the local supply of newly minted science and engineering PhDs and the local demand for technical equipment and services.

Two factors make answering these questions difficult. First, identifying the expenditure-output relationship requires—at a minimum—a large set of controls to disentangle the causal effects from unobservable factors that drive both funding and productivity simultaneously. However, their inclusion sweeps away (helpful) exogenous variation as well, augmenting right-hand side measurement error and exacerbating an errors-in-variables problem that biases estimates towards zero (Adams and Griliches, 1998). Second, researchers rarely directly observe the real value of knowledge production — what Griliches (1979) called the "major difficult[y]" of measuring research output. Publications and patents are helpful for understanding the nature of that production but do not speak to precise amounts of private or social value (Griliches, 1990; Jaffe et al., 2000).

We use exogenous variation in research expenditures to assess the impact of internally funded university R&D expenditures on a set of commonly studied outputs, and then we augment this set with technology licensing revenues to estimate the real value of the resulting innovations. The source of this variation is unexpected National Collegiate Athletic Association Football ("NCAAF") outcomes. Athletic team performance affects cash flow to the university and, in turn, the funds available for research. Even if unobserved school-specific factors that drive research output also influence football team success, they are unlikely to influence *unexpected within-season changes* in team success. Moreover, they are unlikely to be correlated with measurement error in research expenditures, thus mitigating or eliminating the errors-in-variables problem. We measure football team success using the Associated Press Top 25 Poll, and use the difference between postseason and preseason vote counts as the instrumental variable. Since the individual voting results of the poll are made public, and the professional sportswriters who vote have a significant reputation stake in correctly forecasting teams' true prospects, the difference between postseason outcomes and preseason expectations can be treated as random.[7] Also, since each respondent ranks 25 teams, the number receiving positive votes is much larger, ranging between 35 and 52 and averaging about 40.

Three aspects of the setting aid greatly in obtaining results. The first is the great degree to which football impacts overall school finances. Athletics-related revenues derived from the sale of tickets, apparel, broadcasting rights, and trademark licenses provide one channel. These are large in absolute terms (e.g., University of Texas at Austin football revenue tops $150 million each year, seven times higher per game than the median professional baseball team) and in relative terms (e.g., Louisiana State University football revenue is more than one-third of the entire tuition bill). Donations provide another channel that is often tightly tied to football success. As one example, on the night of freshman Johnny Manziel's unexpected Heisman Trophy win, Texas A&M *as a university* raised more money than it typically receives in a month, setting records for quarterly and annual alumni giving.[8] Much of this cash flow is redistributed to the university to fund key activities, including research.[9] The second is the unpredictability of within-season footfall outcomes. The third relates to short lags in knowledge production within the STEM fields. Expenditure data indicates that majority of windfalls/shortfalls are reflected in the budget of the subsequent fiscal year, while patent and license data indicate that faculty gain proof-of-concept and initial private sector interest within that subsequent year. This is consistent with our conversations with administrators, who suggest that marginal funds are often allocated to promising projects hamstrung by funding bottlenecks, as well as technology transfer office ("TTO") reports that indicate aggressive, early protection and promotion of university intellectual property.

We model knowledge production as a function of faculty, facilities, and research support—close analogs to labor, capital, and materials in our setting—as well as a Hicks neutral total factor productivity residual. We assume that the first two inputs are fixed in the short term but the last one is adjustable. The instrument creates unexpected, marginal shifts in the budget used to finance research projects, so it should impact research support only, leaving faculty and facilities unaffected. We show the data is consistent with this, which allows us to isolate the impact of the most contested knowledge production input. In addition, the data provides us with two exogeneity checks. First, we can test whether football success impacts any source of research expenditures other than institutional funds. For example, football should not impact federal grants. Second, we can test if football success impacts contemporaneous R&D expenditures. Since budgets need time to adjust, only subsequent expenditures should be impacted.

These expenditures support research projects. Successful projects yield publications and patents. We estimate the dollar elasticities of scientific productivity for each of these two output measures by two-stage least squares ("2SLS"). When output is measured in articles published, we find an elasticity of 0.28. When measured in patent applications, we find an elasticity around one. All specifications include school fixed effects and school-specific time trends. Standard errors are clustered at the school level, and the estimates are significant at the 5% level. Our 2SLS estimates contrast sharply with lower OLS estimates that result from using the same set of controls. This difference is policy-relevant, since low elasticities could lead to institutional or even national under-investment, and is consistent with speculation by Adams and Griliches (1998), who argued that

[4] Vergan, Dan. USA Today, February 25, 2013, "Science faces sequestration cuts."

[5] Nelson's paper provides fascinating historical perspective on the topic. At the time, the clear comparison to the US was not China but Russia. In fact, the second sentence of that paper states, "since Sputnik it has become almost trite to argue that we are not spending as much on basic scientific research as we should."

[6] For example, an application process for funds within the university may allow for easier transmission of "soft" information.

[7] Readers unfamiliar with the context can consider an injury to a key player as the sort of shock underlying this variation.

[8] Marty Holmes (Vice President, The Association of Former Students, Texas A&M University), telephone conversation with authors, July 2014.

[9] See Dosh (2013) and Lavigne (2014), and the citations therein.

their OLS estimates were unreasonably low (due to input measurement error). Our estimates also exceed those recovered by Jacob and Lefgren (2011), who study federally funded university expenditures, and approximate those recovered by Azoulay et al. (2014), who study federally funded private sector pharmaceutical firm expenditures.

To answer the more fundamental question of whether investments in academic research generate valuable, downstream technology at the margin, we combine the logic of revealed preference with data on university licensing revenues. That is, the amount that unaffiliated, private-sector firms will pay for research output offers a straightforward lower bound on its value. The availability of this measure is a convenient consequence of the fact that universities rarely commercialize their inventions, resulting in intermediate transactions that *price* the technology. When output is measured in upfront licensing revenues, we find an elasticity consistent with approximately constant returns to scale.[10] Adjusted to incorporate recurring "running" revenues, we estimate universities earn much as between 15 and 35 cents on each dollar of research support at the margin. This comes in addition to other private and social benefits (e.g. institutional prestige and spillovers, respectively). Together these findings tend to reject claims that while university-led research produces "paper" returns, it does not generate genuinely valuable innovation at the intensive margin.

This paper contributes to several literatures. It most closely connects to work on the knowledge production function (Griliches, 1979). We build on Adams and Griliches (1998), who measure the impact of university research expenditures on scholarly articles and their citations. They find that adding institution-specific dummy variables yields implausibly low elasticities and argue this is due to right-hand side measurement error, which echoes problems encountered in the larger literature studying input-output relationships among manufacturing concerns. That is, though the research discoveries and manufacturing activities differ in obvious and important ways, with spillovers, large uncertainty, and long lags much more likely among the former than the latter, the inclusion of fixed effects tend to result in very low factor returns in both settings (Griliches and Mairesse, 1998). Olley and Pakes (1996) instead take a control function approach to the problem and find more sensible estimates, although recent work by Collard-Wexler and De Loecker (2016) suggests that the errors-in-variables problems persists, at least when using data from developing countries. In particular, they show that instrumenting for capital with investment produces much higher coefficients than using measured values in Slovenian and Indian datasets. We complement these findings by reaching analogous conclusions exploiting very different variation: in their framework, our instrument would represent a cost shifter, moving the shadow price of materials investments around within the university bureaucracy. As stated above, Jacob and Lefgren (2011) take an IV approach similar to ours, but study federally funded research expenditures instead, while Azoulay et al. (2014) measure the impact of public grants on patenting for private sector pharmaceutical firms. We discuss these results in more detail below.[11]

This paper also closely relates to work assessing the "real effects" of academic research (Acs et al., 1992; Furman and MacGarvie, 2007; Hausman, 2013; Henderson et al., 1998; Jaffe, 1989; Jaffe et al., 1993; Kantor and Whalley, 2014). These papers rely on the geographic coincidence of university activity and private sector outcomes, including wages, employment, and profits. Pakes (1986) provides an alternative approach to directly measuring innovative output, which uses patent renewal decisions to bound the underlying value of inventions. In contrast, we measure impact using technology licensing revenues. These are salient to university faculty and administration (Jensen and Thursby, 2001), but might only capture a fraction of the total returns from STEM research, which more recent research highlights. Using UMETRICS data, which provides detailed accounts of expenditures at a growing list of large US institutions (Allen et al., 2015), Weinberg et al. (2014) show that research support finances not only the training of knowledge workers but also the acquisition of specialized equipment whose very development and production is likely to produce spillovers.[12]

The paper is organized as follows. Section 2 describes the setting, while Section 3 describes the data. Section 4 provides a model of the knowledge production function and the estimation strategy. Section 5 assesses the impact of our instrument on research expenditures. Section 6 estimates the impact of these expenditures on scientific output. Section 7 concludes.

2. Research and development at US universities

2.1. Background

A primary goal of a research university is to increase the pool of available knowledge. Hence, large and successful ones play a key role in economic growth. In the US, universities account for 15% of total R&D spending, which totals nearly $500 billion each year, and more than half of basic science spending.[13] As in most of the developed economies, their share is growing.[14] The US has historically been the global leader in R&D investment, and the productivity of its university scientists and engineers has been viewed as a comparative advantage. However, emerging economies are gaining ground.[15] If knowledge were an easily transported and public good, policymakers could simply free ride off others' investments; however, IP protection and the local nature of many R&D spillovers make these developments serious concerns. In large part, China's aggressive government support of R&D is driving their relative growth. At the same time, as in other developed economies, universities in the US are more and more relying on internal rather than federal, state, or private sector sources to fund R&D.[16]

To create knowledge, universities combine skilled labor with physical capital, and they fund and coordinate research support. For a host of reasons, the policy debate has focused on the last of these, particularly in the STEM fields.[17] The disagreement centers on the magnitude of the return on research expenditures. Proponents of increasing research support point to path-breaking successes that have come out of the university system. Opponents similarly use cherry-picked examples of allegedly useless agendas and obvious research findings as proof of close-to-zero marginal returns. An example is Senator Tom Coburn's annual *Wastebook*, a publication

[10] Our point estimate of 1.86 is within a standard error of one. Returns to scale much above unity are unlikely in this setting.

[11] Payne and Siow (2003) use Congressional Appropriations Committee representation as an instrument for federal funding but do not interpret their estimates as causal effects of federal support separate from other factors. Their instrument has a positive effect on articles but interestingly has no effect—or even a slightly negative effect—on citations per article.

[12] UMETRICS reports payments to and information about employees, vendors, and sub-contractors compensated using federally funded grants, and it can be tied directly to outside data at the level of the individual or the firm. For example, Buffington et al. (2016) link it with the 2010 US Census to study wages by gender. Most striking, they show that while women are paid 31% less overall, the gap shrinks to 11% when controlling for field and funding source and disappears entirely in specifications that include interactions of gender with marital status and family size.

[13] Battelle Memorial Institute. 2014 Global R&D Funding Forecast.

[14] OECD. OECD Reviews of Innovation Policy-Sweden. Organisation for Economic Co-operation and Development, 2013.

[15] Battelle Memorial Institute. 2015 Global R&D Funding Forecast.

[16] OECD Science, Technology and Industry Outlook 2014.

[17] Faculty expenditures are a secondary concern because they partly provide instruction, are mostly fixed over time, and are tied to long-term contracts that make layoffs difficult or impossible. Land, buildings, and large equipment are also largely fixed over time, and large additions are frequently directed investments of individual benefactors.

that enumerates allegations of over-funding. Highlighting the belief that academic recognition doesn't necessarily reflect value, some of the projects scorned in the *Wastebook* did result in scientific publications.[18]

The policy tug-of-war continues. The America COMPETES Act of 2007 represented landmark legislation intended to double the level of essential STEM fields' support, although the budget sequester and ongoing calls for austerity have delayed and reduced the scope of the original legislation. Reauthorization Acts of 2010 and 2015 have not fully reversed those changes. Most recently, the President's 2019 budget proposed deep cuts, including an 11% decrease at the NSF and an 18% decrease at the NIH.[19] In addition, state cuts have provided even greater hurdles for public universities. Highlighting the frustration of administrators at a lack of evidence supporting universities' broad impact, a regent of the University of Wisconsin urged colleagues to "do their 'level best' to use facts and data showing the universities' central role in … stimulating the economy with research and product development."[20]

2.2. The role of football in funding

Since the late 1980s, college football has generated billions of dollars for US universities. It contributes to finances through two channels. The first goes through the athletic department, or more generally auxiliary operations, revenues. Their size can be staggering. At the University of Texas at Austin, football revenues are approaching $150 million each year. For perspective, this is larger than the median professional hockey team (on a per season basis) and many times larger than the median Major League Baseball team (on a per game basis). These revenues are also large relative to other university earning streams. At Louisiana State University and the University of Nebraska, they are nearly one-third the size of the entire tuition bill. For many schools—the majority of those in our panel—football generates more revenue than all other sports combined.

The second channel is alumni donations. Football success is a major catalyst for philanthropic fundraising shocks (Anderson, 2012; Meer and Rosen, 2009). For example, Texas A&M University raised more money the night after its freshman quarterback, Johnny Manziel, won the Heisman Trophy than it typically raises in a full month. That year, the school announced it received a record-setting $740 million in donations.[21] The university chancellor John Sharp highlighted the significant role college football played in their fund-raising efforts, stating, "football is one heck of a megaphone for us to tell our story."[22] Philanthropy represents an important source of university science funding overall and the majority of its recent growth (Murray, 2013). Moreover, schools can also directly tie athletic privileges to academic donations. In March 2015, two months after winning the National Championship, Ohio State notified fans that a $3000–5000 donation to the university fund was necessary to purchase a parking pass for the following season (on top of the standard $375 cost). This move was expected to generate $18 million in contributions.[23] Stinson and Howard (2014) document how one large Midwestern school makes donors of academic gifts over $3000 eligible to buy season tickets.

The success underlying these contributions are volatile. More than half of the schools in our panel, described in the following section, have competed for the national championship—that is, ranked #1 or #2 in the country—at some point between 1987 and 2012. Yet every one of these teams was unranked at some other point over the same period. Within-season reversals of fortune are just as common. Almost a quarter of teams finishing first or second began the season outside the top ten, and nearly as many beginning first or second finished outside the top ten.

A share of these revenues and donations are returned to the general university fund and ultimately support academic endeavors. For example, in 2012, the Louisiana State University team pledged over $36 million over 5 years to support the school's academic mission. In 2005, the Notre Dame football used $14.5 million of its postseason bowl winnings to fund "academic priorities" including "library acquisitions and purchasing of scientific instruments."[24] In 2011 and 2012, the University of Florida team gave $6 million to cover shortfalls in university funding (Dosh, 2013). From 2012 to 2013, the University of Texas - Austin gave $9.2 million of its $18.9 million football surplus back to the university fund while the University of Nebraska - Lincoln did the same with $2.7 million of its $5.2 million surplus (Lavigne, 2014). Also consistent with this notion, E. Gordon Gee, former President of The Ohio State University, stated that "we took direct dollars from the athletic budget and put it into academic programs."[25]

Fig. 1 suggests many of these dollars support research. The x-axis provides a standardized measure of unexpected college football outcomes.[26] The y-axis measures the log of school funded research support expenditures in the subsequent year. Plotted points represent residuals binned according to their x-axis values, after accounting for school fixed effects and school-specific time trends. The result is an unambiguous positive relationship and the primary motivation for using unexpected within-season vote changes as an instrument for subsequent year research support expenditures. These and related results are revisited below.

3. Data

3.1. Sources

The data come from several sources. The instrument is derived from Associated Press Top 25 Poll ("AP Poll") vote data. The poll surveys sixty-five sportswriters and sports broadcasters. Each provides a ranking for the top twenty-five teams from NCAAF Division I. Each team receives 25 points for each 1st place vote, 24 points for each 2nd place vote, and so forth, and the votes are aggregated over survey responses.[27] The AP publishes the vote totals of all

[18] For example, the 2014 *Wastebook* cites a $856,000 NSF grant devoted to studying whether a mountain lion can be taught to use a treadmill. (The answer is yes, but it takes eight months.) The *Wastebook* then points out that this research was published in the *Journal of Neural Engineering*. We note that this was a misrepresentation of the work.

[19] Reardon, Sara and Tollefson, Jeff and Witze, Alexandra and Ross, Erin. May 23, 2017. "Trump budget would slash science programmes across government." https://www.nature.com/news/trump-budget-would-slash-science-programmes-across-government-1.22036 (retrieved March 3, 2018).

[20] Simmons, Dan. February 6, 2015. "Rebecca Blank: Scott Walker's budget would mean $91 million budget hole at UW-Madison." http://host.madison.com/news/local/education/university/rebecca-blank-scott-walker-s-budget-would-mean-million-budget/article_52c6749b-4cc9-53bb-b07e-83c3f227c23c.html (retrieved November 3, 2015).

[21] Holmes, personal communication, July 11, 2014

[22] Troop, Don. "Texas A&M Pulls in $740-Million for Academics and Football." The Chronicle of Higher Education, September 16, 2013. http://chronicle.com/blogs/bottomline/texas-am-pulls-in-740-million-for-academics-and-football/ (accessed December 2, 2014).

[23] Bischoff, Laura A. "OSU to enforce tailgating rules." Dayton Daily News, September 4, 2015. The author points out that this was, in fact, a long-standing policy but was previously never enforced.

[24] See Dosh (2013) pp. 139.

[25] "Dropping The Ball: The Shady Side Of Big-Time College Sports," The Bob Edwards Show (Washington D.C.: Public Radio International, January 4, 2015).

[26] More detail is provided in the subsequent section.

[27] The exceptions are 1987 and 1988, when voters ranked only the top 20 teams. For these polls, teams received 20 points for each 1st place vote, 19 points for each 2nd place vote, and so forth.

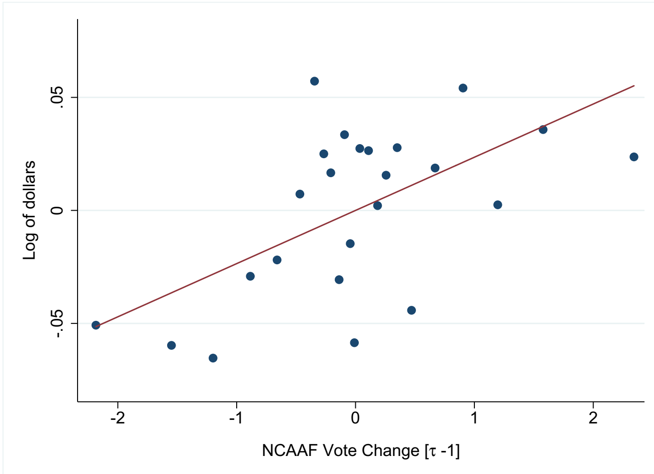

Fig. 1. Football impacts school funded research support expenditures. Note: The x-axis measures within-season changes in Associated Press Top 25 Poll votes in standard deviations. The y-axis measures the log of school funded research support expenditures in the subsequent year. Plotted values are residuals after controlling for school fixed effects and school-specific time trends. Observations are "binned" according to their x-axis values.

teams. Ballots are collected weekly through the season, with results made public and published at the end of the week. We measure the within-season change in team quality by subtracting preseason votes from postseason votes. Polls varied slightly in the number of voters and, in 1987 and 1988, the number of points allocated, so we normalize the measure by standard deviation. This data is widely disseminated each week of the season and have a special place in college football; unlike professional sports or other college athletics, which rely on playoffs and divisional rank and record, polls were the sole source of determining an NCAAF champion until 2013.[28] At least three other polls are widely published, although the AP Poll is the best known and longest running. Moreover, although they are closely correlated with the AP Poll, the other major polls had obvious limitations for our setting.[29] The relevant time variable for this data is the fiscal year in which a season is wholly contained. Fiscal years coincide with the academic calendar for schools in our data.

There are three types of input expenditures. All are in terms of constant 2009 dollars. Separately budgeted research and development expenditures ("research support") data come from the annual NSF Higher Education Research and Development Survey. This covers all science and engineering R&D that is *separately budgeted and accounted for*.[30] The survey spans all institutions spending at least $150,000 in separately budgeted R&D and breaks expenditures down by source (federal government, state/local government, institution, business, and other). Responses are carefully reviewed and verified as needed.[31] The other two, faculty and facility expenditures, come from the Integrated Postsecondary Education Data System (IPEDS).[32,33] Faculty headcount and salaries cover all tenure-track and tenured faculty employed in fall quarter. Facilities comprise all plants, property, and equipment less depreciation at fiscal year-end.

There are three measures of research productivity. Article counts are provided by the Thomson-Reuters Incites database. Observations are at the academic institution, calendar year, scientific field level. Incites provides two field classification systems, Essential Science Indicators ("ESI") and Web of Science ("WoS"). To robustly measure productivity, we consider basic and applied science article measures created from both.[34] New patent application counts are provided by the US Patent and Trademark Office.[35] We assign to an academic institution any filing where the institution appears as an assignee, which we observed using the PatentsView dataset. Observations are at the academic institution, calendar year level. Technology licensing revenue is provided by the Association of University Technology Managers ("AUTM"), which administers annual surveys. The respondents are staff of university TTOs, groups responsible for licensing and managing the intellectual property created by faculty. TTOs are rewarded for completing the survey by receiving data on all other institutions, so while completion is not compulsory, non-response is rare once schools begin reporting. Observations are at the academic institution, calendar year level.[36] Most licensing deals stipulate a stream of payments rather than a one-time cash transfer, so TTO revenue in any year is swamped by prior licensing activity. AUTM, fortunately, separates "running royalties," i.e. those tied to product sales, from the totals. Thus, we construct our output measure as total licensing income, net of the portion passed through to other parties, multiplied by one minus the ratio of running royalties to total licensing income. AUTM also collects the year each TTO was established, so they avoid mis-classifying some observations as zero. In a few cases, AUTM data required supplementary information, e.g. TTO annual reports. For example, UCLA is not separated from other members in the California system, though the state publishes the figure separately. The appendix provides more detail.

3.2. Length and scope

The beginning of the panel coincides with the start of the "modern era" of college football and covers the period of exploding popularity

[28] In 2014, a playoff system was instituted.

[29] The BCS Poll, for example, did not cover our sample. Other polls are less widely know and relied upon.

[30] As per Office of Management and Budget survey B.1.b and A21 (revised), this comprises sponsored research funding (from both federal and non-federal entities) and university research funding (for which there was an internal application for the funds). It excludes instruction and related departmental expenditures.

[31] In cases where we expected there was a response error, we asked the NSF for clarification, which had itself already asked the institution for clarification. We thank Ronda Britt at the NCSES, who was particularly helpful in this regard.

[32] IPEDS aggregates departments, so we cannot separate out the science and engineering faculty. However, they are the majority. For instance, about 62% and 68% of Penn. State and Ohio State faculty were in science and engineering departments, respectively, in 2013. We also expect departments to be highly correlated within school. We also cannot separate out facilities devoted to research from those devoted to instruction, administration, and other enterprises. However, anecdotally, we expect athletics-related cash shocks to affect auxiliary and student-related functions of the school at least as much as research. Hence, it suffices to show no aggregate impact on facilities to conclude there is no impact on the research-related portion.

[33] IPEDS lacks facility data in 1990, 2001, for all public schools in 2000, and in a small number of other observations (about 1% of the sample) and faculty data in 2001. We impute missing facility and faculty data, though doing so never meaningfully impacts any estimates of the parameter of interest.

[34] In ESI, our basic science fields include biology & biochemistry, chemistry, computer science, environment/ecology, space science, mathematics, physics, and microbiology. Applied fields additionally include engineering, plant & animal science, and agricultural science. WoS are defined similarly. Details are in the appendix.

[35] Note that our use of the word "patents" or "patentable idea" is for the sake of brevity only. Not all patent applications turn into patents. The cost of filing—mainly legal fees—is high, so universities like assurances that an idea is patentable before engaging attorneys. Technically, what we measure is the cost of generating an idea that merits filing an application.

[36] Precise timing in AUTM data is unclear. Annual editions of the survey are distinguished by subtitles that state the fiscal year, though AUTM instructions only state (using 2016 as an example), "the Survey requests data for a complete year regardless of your internal reporting or fiscal year. The 2016 reporting period may be any 12 month period ending in calendar year 2016." To partially resolve this, we exploit the fact that AUTM also asks about patenting activity. (The data are much less complete than the USPTO's administrative records, which is why we rely on the latter, though this still provides a point of comparison.) AUTM more closely resembles calendar year than June or September year end reporting.

Table 1
Summary statistics.

	N	Mean	Median	Std. Deviation
Faculty salaries	1040	107,411.80	95,178.80	52,437.55
Faculty headcount	1040	1178.25	1057.00	475.91
Facility expenditures	1070	1301.41	1010.71	1096.44
Total research support	1072	332,726.55	273,092.41	246,920.42
Institutional research support	1072	78,219.16	60,451.63	60,602.87
Federal research support	1072	186,098.60	126,639.03	167,627.04
Business and other research support	1072	27,852.91	17,951.54	29,515.90
State and local government research support	1072	40,555.88	27,854.35	39,977.45
Basic science articles (ESI field definitions)	1080	806.18	632.00	625.39
Basic science articles (WoS field definitions)	1080	658.08	511.00	508.38
Applied science articles (ESI field definitions)	1080	1157.70	927.00	821.92
Applied science articles (WoS field definitions)	1080	929.38	705.00	725.82
Patent applications	1080	44.11	26.00	52.73
Licensing revenue, up-front	1005	1826.15	683.60	3464.96

Research support, faculty salaries, and licensing revenues are reported in thousands of US dollars. Facility expenditures are reported in millions of US dollars. There are a maximum of 1080 observations for the full panel, though certain variables are unavailable for certain years.

and profitability of the sport, more than sufficiently large to shift universities budgets. It begins with the 1984 Supreme Court ruling in *NCAA v. Board of Regents of the University of Oklahoma*.[37] Prior to this ruling, the NCAA restricted the number of games that could be broadcast, threatening non-complying schools with an association-wide boycott. The Burger court ruled that the NCAA violated antitrust laws by controlling television broadcasting rights, so schools and their conferences were free to negotiate directly with broadcasters. Broadcast networks treated the first year or two as a trial for the new arrangement, but by 1987 the number of televised games and the exposure of the league surged, leading to unprecedented gains.[38]

Publishing-related estimates reflect the full panel. Patenting-related estimates do, as well. However, harmonization of the US patent system in 1995 prompted an increase in overall applications in 1996, so to assess robustness we also provide patenting-related estimates that reflect a start year of 1996 as well as a start year midway between the beginning of the full panel and 1996. Licensing-related estimates reflect a start year of 1993, since AUTM data is unreliably reported prior to this.

The panel cross section covers forty schools.[39] The median team receives zero votes in a poll, so using the universe of teams would result in a large number of zeros in the instrument. Thus, we order the schools in terms of their total variation in the instrument and select the forty largest, i.e. one-third of the 120 NCAAF Division I teams. The resulting list includes most large public universities and is quite close to merely selecting the most successful NCAAF programs over the past three decades. It includes private (e.g. Stanford, Notre Dame) and public (e.g. Alabama, Nebraska) institutions.[40]

3.3. Summary statistics

Table 1 provides a summary of the data. First, there is a great deal of variation in both inputs and outputs. Standard deviations are in the neighborhood of the mean values for most variables. There is also considerable right skew, so most of our analysis uses log transformations of left- and right-hand side variables. Schools in our panel contribute about a quarter of the over $300 million in total annual average research support. The majority of this support comes from the federal government (e.g., the NSF, NIH, and Departments of Defense and Energy). Schools average roughly 1200 faculty. Mean and median salaries average just above and below $100,000, respectively. Facilities are valued just above $1.3 billion. Schools produce between about 700 and 800 basic science articles each year. Including applied science fields (e.g., engineering, plant and animal science, etc.), schools produce between about 900 and 1100 articles/year. Schools also average 44 patentable ideas and upfront licensing revenues of $1.8 million annually.

Some observations have missing values or errors. Faculty salaries and headcounts are unavailable in 2001 due to an agency budget cut that temporarily suspended the survey program. Facility expenditures are missing for 1990, which precedes the survey, for 2000, since the survey was not administered in this year, and in 2016. Eight research support expenditure observations contain erroneous information; these are dropped, and the observations are assumed missing at random. Licensing revenue is missing in five cases.[41]

4. Empirical framework

4.1. Model

The knowledge production function (Griliches, 1979) of university i in period t is given by $Y_{it} = A_{it}F(L_{it}, K_{it}, M_{it})$. The function takes as its arguments L, K, and M, which for our purposes represent faculty, facilities, and research support, as well as a Hicks neutral

[37] See *NCAA v. Board of Regents of the University of Oklahoma*, 468 US 85 (1984).

[38] That year featured the highly contentious Fiesta Bowl, which became one of the most watched college games in history. The game pitted Penn State against a heavily-favored University of Miami. The pre-game antics of Miami, including dressing in military fatigues for the flight to the game, and controversial remarks by both sides at a joint team dinner the night before the game contributed to wide-spread media attention. For the first time in history, a sitting US President (Ronald Reagan) was interviewed at the halftime show. Penn State won 14–10.

[39] To assess external validity, we construct an auxiliary panel of forty additional research-activity schools and then compare the levels of and relationships between inputs and outputs in the auxiliary panel to those in the panel. We report the results of these exercises in the appendix and summarize them in Section 6.

[40] Four schools systematically lacked data and were excluded. Boise State University and Brigham Young University did not report institutional research expenditures intermittently. Texas Christian University never reports licensing revenue. Midway through the panel Syracuse stops reporting licensing revenue.

[41] The University of Texas at Austin stops reporting campus-specific figures to AUTM in 2009, though it continues to disclose these figures in TTO annual reports. In 2013, survey respondents for the University of Wisconsin–Madison erroneously entered running revenues as total revenues or vice versa in 2013. The reported items are equal but should not be, evidenced by substantial new licensing activity in that year.) In 2015, the University of Michigan erroneously failed to report monetized payments related to a drug for Gaucher Disease as running revenues, which was apparent from comparisons to their TTO annual reports.

Table 2
The effect of athletics outcomes on expenditures, by expenditure type.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	Inst. res. support	Faculty salaries	Faculty salaries	Faculty headcount	Faculty headcount	Facility expend.	Facility expend.
NCAAF Vote change [$\tau-1$]	0.0238***	−0.000515		−1.46e−06		−0.0034	
	(0.00587)	(0.00152)		(0.00272)		(0.00615)	
NCAAF Vote change [$\tau-2$]			−0.00271*		−0.00166		0.00142
			(0.00149)		(0.00191)		(0.00506)
Observations	1070	1080	1080	1040	1040	1080	1080
R-squared	0.94	0.987	0.987	0.982	0.982	0.993	0.993

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
The right-hand side variable is the instrument, i.e. the difference between preseason and postseason NCAAF Top 25 Poll votes in standard deviations. The $\tau-2$ row lags the right-hand side variable one additional period. The left-hand side variables are log values of expenditures, by type. All specifications include school fixed effects and school-specific time trends. Standard errors are clustered at the school level.

"total factor" productivity shock (Syverson, 2011). If the function is Cobb-Douglas, then taking logs yields

$$y_{it} = a_{it} + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it}. \tag{1}$$

The total factor productivity shock is a linear function of controls, denoted W, and a residual so that $a_{it} = W_{it}\Lambda + \epsilon_{it}$. W_{it} comprises school fixed effects and school-specific time trends.

We are interested in β_m.[42] Estimating the parameter from Eq. (1) is not straightforward. If administrators choose high m when ϵ is large, then the key right-hand side observable is determined endogenously. Moreover, if the university is liquidity constrained—the conjecture that motivates this analysis in the first place—then a factor outside the model could drive both funding access and the total factor productivity residual simultaneously. Rather than place considerably more structure on the problem, we use an instrument, denoted z, to exogenously shift m.

Since the hiring and firing of faculty and the construction and demolition of facilities are very slow, L and K are fixed in the short-term. Research support, on the other hand, consists of things like laboratory materials, non-faculty research personnel, and software. These are likely to be adjustable. Therefore, we assume the instrument will not affect faculty or facilities, but will affect research support. This allows us to isolate the impact of the last of these inputs. One clear concern, in the event this is wrong, is that schools with cash windfalls poach faculty from less fortunate schools and that this behavior is the real driver of output changes. The data support our assumption, which we show in the following section.

Measurement error in the right-hand side variables of Eq. (1) is also problematic. If the econometrician sees only $\tilde{x}$, which equals expenditure x measured with i.i.d. noise e_x, then regressing output on observed input expenditures results in downward bias. Moreover, the degree of this bias may be highly dependent on the type of controls included in the econometric specification—the richness of W_{it}—since conditioning variables will sweep away potentially helpful exogenous variation along with the unobservables.[43] This creates serious problems in practice (Griliches and Mairesse, 1998).[44]

Again, we rely on our instrument. It is unlikely to be correlated with measurement, so resulting estimates will be unbiased.

4.2. Estimating equations

We begin by estimating a linear effect of the instrument on expenditures, by type, which are measured with error. The estimating equations are given by

$$\tilde{x}_{it} = W_{it}\Gamma_x + \alpha_x z_{it} + \omega_{xit}, \tag{2}$$

where $\tilde{x}$ equals $\tilde{l}$, $\tilde{k}$, or $\tilde{m}$ As shown in the following section, the data indicate α_x is near zero for labor and capital but is not zero for research support. Thus, we henceforth assume that the instrument is independent of facility expenditures and faculty salaries.

Our first stage estimating equation is given by

$$\tilde{m}_{it} = W_{it}\Psi + \gamma\tilde{l}_{it} + \delta\tilde{k}_{it} + \lambda z_{it} + \eta_{it}. \tag{3}$$

The exclusion restriction requires that while unobserved productivity shocks (ϵ) may enter Eq. (3) through the residual (η), the shocks are independent of z. We argue that violations of this restriction due to endogeneity are unlikely. College football outcomes are unlikely to directly influence the residual of research productivity, either in the laboratory or publishing stage. For example, effects on the mood of faculty or attitude of referees are second order relative to the effects of providing extra funds to cash-strapped scientists and engineers. Concerns due to simultaneity are even smaller. To bias results, unobservable factors that impact subsequent research productivity would need to do one of the following: either arise unexpectedly within the season and immediately influence football outcomes or go unnoticed by Associated Press voters. However, the twenty-week within-season window is very short, and the reputations of the sportscasters and sportswriters who vote in the poll depend on informed and accurate predictions.[45]

Our second stage estimating equation is given by

$$y_{it} = W_{it}\Phi + \psi\tilde{l}_{it} + \chi\tilde{k}_{it} + \theta\hat{m}_{it} + \mu_{it}, \tag{4}$$

where $\hat{m}$ denotes predicted values of research support based on estimates obtained from Eq. (3). Conditional on $\tilde{l}$, $\tilde{k}$, and W, changes in $\hat{m}$ are determined by shifts in z, which are independent of measurement error research support and the unobserved productivity shock. Thus, while m might be partly determined by ϵ, and while $\tilde{m}$ might

[42] β_m is the center of the policy debate due to factors described in Footnote 17. It is also the one that our research design allows us to reliably recover.

[43] Consider, for example, school fixed effects. These control for time-invariant unobservables that, for instance, afford Stanford both generous funding and high output relative to other schools in the panel, but also force the researcher to ignore any informational content in the fact that Stanford has a high level of funding.

[44] The sensible elasticities that the "control function" approach produced using US private sector data (Olley and Pakes, 1996) temporarily reduced interest in the errors-in-variables problem, but recent research suggests this problem still persists, especially using non-US data (Collard-Wexler and De Loecker, 2016). Our results below will indicate this problem extends to university R&D input-output data.

[45] A more nuanced issue is that the instrument is constructed as a difference, so its expectation may depend on preseason votes, though this is not a problem for this setting.

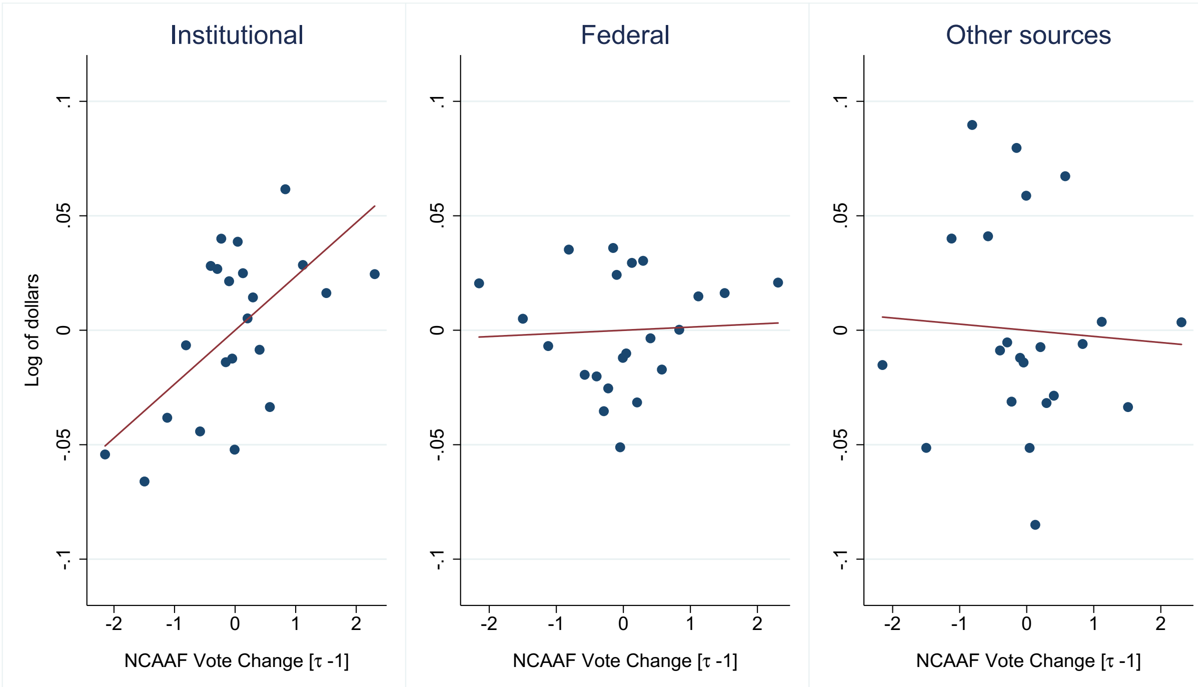

Fig. 2. Football does not meaningfully affect support from federal or other sources. Note: The x-axis measures within-season changes in Associated Press Top 25 Poll votes in standard deviations. The y-axis measures the log of research support expenditures, by source. In the right, middle, and left panels, the sources are the institutions themselves, the federal government, and other sources (industry as well as state and local government), respectively. Plotted values are residuals after removing school fixed effects and school-specific time trends. Observations are then "binned" according to x-axis values. The left panel is identical to the prior figure and considers the impact on school funded expenditures. The middle and right panels consider the impact on support funded by the federal government and other sources, respectively.

be partly determined by e_m, neither enter $\hat{m}$. As a result, θ provides an unbiased estimate of β_m.

4.3. Timing summary

In the model, t subscripts denote periods in the abstract and thus merely summarize the relationship between the instrument, expenditures, and outputs and do not explicitly reference calendar time. Budgeting, experimenting, and publishing take time, resulting in delays that create lags between the *measured* values. Our main specifications reflect the following timing.

In fiscal year τ, teams play out the season from mid-August to early-January and generate values for the instrument. Realizations drive cash flows from sources such as apparel sales, playoff appearance payouts, and donations, in time to shift the subsequent fiscal year's budget and locate highest-return projects. Survey data show that insufficient/decreased R&D support poses the largest challenge for research faculty,[46] suggesting both an abundance of projects bottlenecked by money and a high likelihood that marginal funds are spent close to when budgets are replenished. Hence, in the next period, fiscal year $\tau + 1$, budgets adjust and faculty conduct research.

As soon as results provide proof of concept, faculty are encouraged to protect their ideas and TTOs are motivated to license them. Thus, we assume new patent applications are filed and licensing deals are consummated in calendar year $\tau + 1$. (We shift calendar year reporting for our output measures due to data constraints. Note that this shift adds an additional six month lag between inputs and outputs.) In the subsequent period, calendar year $\tau + 2$, faculty publish articles. The input-output lags reflect a host of institutional—typically STEM-specific—factors and seem fast to individuals familiar with the social sciences, so we return to this issue in detail below.

[46] Battelle Memorial Institute. 2014 Global R&D Funding Forecast.

5. Athletics outcomes and research expenditures

5.1. Magnitudes, by input

Table 2 shows that unexpected college football outcomes are a strong predictor of research support expenditures but have no impact on faculty or facilities. Each specification in the table accounts includes school fixed effects and school-specific time trends, and allows for arbitrarily correlated standard errors within a university over time. The first column provides the coefficient estimates from the regression in Fig. 1. A one standard deviation change in the instrument translates to a 2.4% increase in the support. The estimate is significant at the 99% level, and the corresponding F-statistic is 20. To put the result in perspective using round numbers, a 1000 vote change amounts to moving from 17th place to 1st or from unranked to 10th. This represents a 2.2 standard deviation change in votes. The estimates indicate this results in a $1.7 million increase in support.

The next column shows a near-zero effect on faculty salaries. The point estimates as well as the standard errors are very small, helping to rule out any impact of the instrument on these outcomes. One concern is that faculty expenditures may require an additional period to adjust, so the effect is present but lagged one more year. Column 3 rules this out. For robustness, columns 4 and 5 substitute faculty headcount, which may be a more sensitive measure of the input, for salaries. The results are similar.[47] The final two columns indicate zero

[47] These measures reflect survey questions that ask about individuals holding the title of "professor" (regardless of tenure). Research staff and graduate students, whose compensation falls under research support expenditures, are separately surveyed. We use additional data to assess whether unexpected NCAAF outcomes affect these individuals' employment, and we report the results in the appendix. The instrument affects research staff but not graduate students, consistent with the latter (human capital) input representing a longer term financial commitment on behalf of the school.

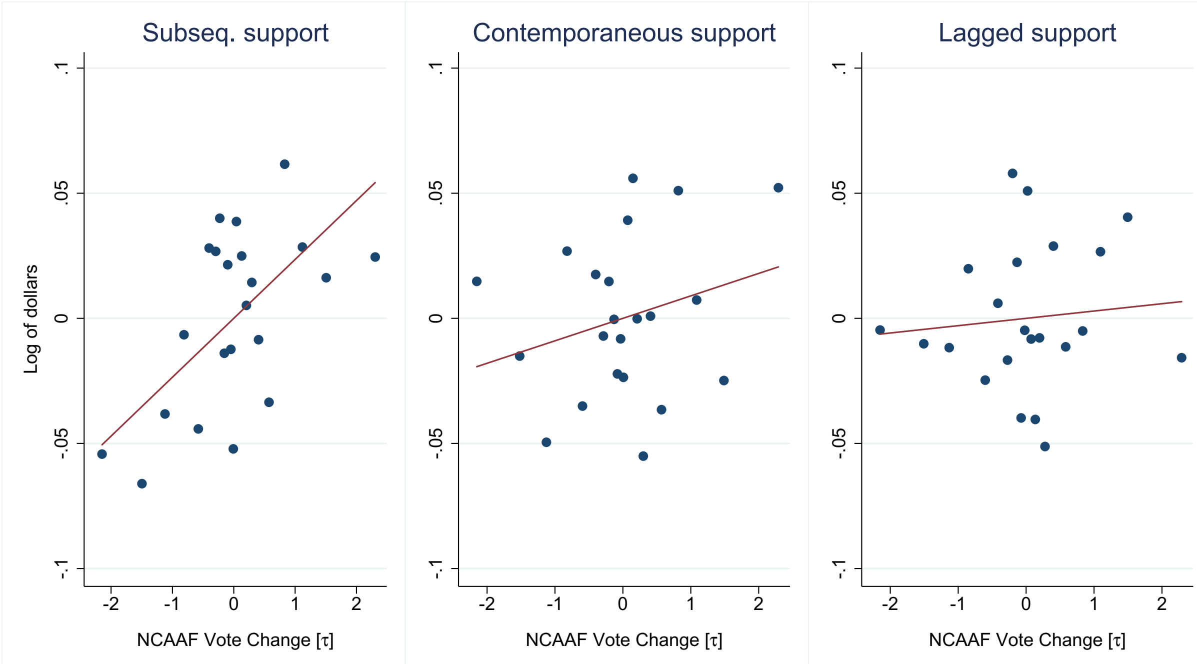

Fig. 3. Football does not meaningfully affect support in contemporaneous or lagged periods. Note: The x-axis measures within-season changes in Associated Press Top 25 Poll votes in standard deviations. The y-axis measures the log of school funded research support expenditures. The left, middle, and right panels show the impact to expenditures in the subsequent period to the football season, the contemporaneous period, and the period prior, respectively. Plotted values are residuals after removing school fixed effects and school-specific time trends, which are then "binned" according to x-axis values. The left panel is identical to the prior figure and considers the impact on subsequent year expenditures. The middle and right panels consider the impact on contemporaneous and lagged expenditures, respectively.

impact on facilities. While the standard errors are larger here, we emphasize that the *lower bound* of the 95% confidence interval on research support is greater than the *upper bound* on the interval of the other inputs, regardless of the timing or measure.[48]

Note that when output is measured by licensing revenues, there is an additional concern. Even if our budget variation does not induce faculty hiring, it may lead to investments in more TTO staff or better counsel, and ultimately a simultaneous rise in licensing. Fortunately, AUTM collects supplementary data on TTO employment and legal fees, and in the appendix we show that the instrument has no effect on these outcomes.[49]

5.2. Exogeneity checks

The NSF data breaks down research support by source. So far, we have considered only support provided by the school. Although football should impact school funded support, it should not impact money coming from the federal government or other sources not affiliated with the institution. Testing this provides a check on the exogeneity of the instrument. Fig. 2 shows that the data is consistent with this. The left panel duplicates Fig. 1 and is provided only for graphical comparison. The middle and right panels plot the same relationship, but with the left-hand side variable measuring support from the federal government and other sources, respectively, rather than from the school itself.[50] The coefficients on the latter two funding sources are near zero, with the federal expenditures in particular being very precisely estimated near zero.

Since the football season cannot impact support that has already been budgeted, football should not impact contemporaneous or past expenditures. Fig. 3 shows the data is consistent with this, too. Once again, the left panel duplicates Fig. 1. The middle and right panels plot the instrument against contemporaneous and lagged school funded research support expenditures, respectively, and unlike the left panel, these show a slope nearer to zero and an order of magnitude smaller.

5.3. Timing of expenditures

We also assume that fiscal year τ football season principally funds research in fiscal year $\tau + 1$. That is, expenditures are lagged one year. To test the appropriateness of this assumption, we regress the log of research expenditures on the instrument lagged one, two, three, and four additional years. We report the relevant results in the appendix. We find that the coefficient on the instrument lagged one year is typically twice the size of the other coefficients and is often much higher. Further, while that coefficient is significant at the 99% level, only one other coefficient is significant at even the 10% level.

These results square with intuition. The season concludes in the first days of January, providing nearly six months for the subsequent year's budget to reflect cash flow changes affected by the team's success. Moreover, budgets replenish at the start of the fiscal year, which conveniently corresponds to a period when students are on break.

[48] To be clear, these findings do not imply that unexpected athletics outcomes leave all other attributes and activities of the schools aside from institutional research support unaffected. We expect, for example, an effect on subsequent undergraduate applications, i.e. a "Flutie effect," and there is evidence of this in the IPEDS data. We only require that these non-research related changes do not impact scientific productivity, which is a point we return to below.

[49] We thank Alberto Galasso, Emir Kamenica, and Dennis Yao for suggestions that led to this test.

[50] The other sources include state and local governments, firms, and entities the NSF cannot cleanly fit into one of these categories. Running on each individually does not change the zero-coefficient result.

Table 3
Pus.

Variables	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV	(6) IV	(7) IV	(8) IV
Institutional research support [$\tau - 1$]	0.044**	0.0491**	0.0514**	0.0576**	0.127	0.173*	0.18*	0.281**
	(0.0166)	(0.0189)	(0.0206)	(0.0276)	(0.0816)	(0.0933)	(0.0977)	(0.119)
Facility expenditures [$\tau - 1$]	0.0179	0.017	0.0204	0.0318	0.0215	0.0223	0.0259	0.0415
	(0.0218)	(0.0244)	(0.0249)	(0.0278)	(0.0215)	(0.0244)	(0.0235)	(0.0335)
Faculty salaries [$\tau - 1$]	0.105**	0.0816	0.0821	0.0717	0.0646	0.0212	0.0196	−0.0371
	(0.0512)	(0.0628)	(0.0706)	(0.0686)	(0.0612)	(0.0715)	(0.0782)	(0.0793)
Observations	1071	1071	1071	1071	1071	1071	1071	1071
R-squared	0.992	0.991	0.991	0.988	0.992	0.989	0.989	0.983
Publication type	All	All	Basic	Basic	All	All	Basic	Basic
Scientific field defintions	ESI	WoS	ESI	WoS	ESI	WoS	ESI	WoS
F-Stat: 1st Stage					19.97	19.97	19.97	19.97

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
The right-hand side variables are the logs of lagged faculty salaries, facility expenditures, and institutional research support, the last of which takes predicted values in columns 5-8. The left-hand side variable is the log of articles. All specifications include school fixed effects and school-specific time trends. Standard errors are clustered at the school level. The last row reports the first stage F-statistic for the instrument. "Publication type" denotes whether the estimates reflect basic or applied science article counts. "Scientific field definitions" denotes whether basic and applied science article counts used Essential Science Indicators ("ESI") or Web of Science ("WOS") field definitions.

Thus, with survey data indicating funds are the most frequent bottleneck in the research process and with classes not in session, much of the year's research may take place in early summer, and is unlikely to be delayed to another period.[51]

6. Main results

6.1. Articles

We now turn to our main results. Table 3 reports estimates from Eq. (4) when output is measured in log articles published. We find an elasticity with respect to institutional research support of between 0.17 and 0.28 depending on the scope and definition of the fields. Incorporating applied fields, particularly under the ESI definitions, yields lower estimates, presumably reflecting many publications originating in medical schools, whose relative independence makes them less sensitive to athletic-related funding changes.[52] The F-statistic on the excluded instrument is 20.0. OLS estimates are much lower, though they are very near those recovered by Adams and Griliches (1998), who use an analogous dataset covering an earlier period.

Facility expenditures and faculty salaries represent control variables in Eq. (4). Their respective coefficients are included only for the sake of comparison. Relatively small and insignificant effects should not be taken to indicate that faculty and facilities are unimportant to knowledge production — rather that these inputs likely suffer the same measurement right-hand side measurement challenges as institutional research support.

Figures reported in the top row provide a stark contrast to prior 2SLS estimates specific to federally funded expenditures. Jacob and Lefgren (2011) show that NIH grants worth $1.7 million translate to less than one additional publication over the following five years.[53] Provided that federal research grants are spent on a combination of faculty, facilities, and support, one would expect this figure to be lower than one predicted by our estimates, since the marginal product of a dollar optimally allocated across inputs is higher than the marginal product of a dollar allocated to a single input. Yet according to Table 3, publications cost only a fraction of this amount using institutional funds. It is unclear what drives this difference, although Jacob and Lefgren (2011) offer one clever explanation: their low estimates reflect a competitive funding environment. In other words, the type of projects marginally missing NIH funding due to statutory quirks easily find alternate sources of money. In our context, high estimates may reflect university administrators selecting inherently promising projects that do not look appealing in the arm's-length federal grant process.

6.2. Patents

Table 4 reports estimates from Eq. (4) when output is measured in log patent applications filed. When we consider the full sample, we find an elasticity with respect to institutional research support of 1.22, consistent with approximately constant returns to scale.[54] Similar point estimates and standard errors obtain when we use alternate start dates so that, for example, the sample is restricted to observations after the 1995 change in the patent filing laws. The F-statistic on the excluded instrument is 18 for the full panel, though first stage power falls as we restrict the sample, which is not surprising. As in the prior table, IV estimates again are much higher than OLS ones — in both cases, they are four or five times as large. Coefficients on faculty salaries and facility expenditures are again not statistically distinct from zero.

These estimates translate to reasonable costs in dollar terms. Using the number of patents and the level of institutional research support in the final year of the panel and assuming constant returns to scale, the cost of generating a patentable idea is $2.59 million.[55] The number is close to—though still somewhat smaller than—the $4.35 million figure that Azoulay et al. (2014) arrive at (which is based on federal funding provided to private sector pharmaceutical and biotechnology firms).

[51] Battelle Memorial Institute. 2014 Global R&D Funding Forecast.

[52] For example, ESI does not separate biomedical engineering from other, non-clinical engineering subfields.

[53] Payne and Siow (2003) use alumni representation on the US Congressional appropriations committees to derive variation in federal university funding. Their instrument drives research support *and* other expenditures, so they interpret their coefficients as "the total change in output when an institution obtains an additional unit of the input that may be correlated with other inputs that affect the output measure."

[54] Increasing returns are unlikely in this setting. We return to this point below in more detail when we discuss licensing.

[55] This approach is inconsistent with the Cobb-Douglas functional form specified in the model, since the latter is non-linear in the inputs. Hence, for robustness we also re-estimate the first and second stage in levels rather than logs. In lieu of a more detailed discussion about the relative merits of the approaches, we note that these yield approximately similar results.

Table 4
Patenting estimates.

Variables	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Institutional research support [τ]	0.24*	0.22**	0.243**	10.21*	10.42**	10.22**
	(0.138)	(0.101)	(0.105)	(0.686)	(0.626)	(0.607)
Facility expenditures [τ]	−0.203*	−0.16	−0.125	−0.146	−0.0653	−0.0598
	(0.111)	(0.0972)	(0.106)	(0.131)	(0.145)	(0.141)
Faculty salaries [τ]	0.167	0.0978	0.0336	−0.128	−0.332	−0.357
	(0.328)	(0.292)	(0.338)	(0.408)	(0.467)	(0.466)
Observations	797	948	1,018	797	948	1,018
R-squared	0.894	0.884	0.875	0.869	0.835	0.84
Panel start	1996	1992	1990	1996	1992	1990
F-Stat: 1st Stage				9.053	13.79	17.62

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
The right-hand side variables are the logs of faculty salaries, facility expenditures, and institutional research support, the last of which takes predicted values in columns 4-6. The left-hand side variable is the log of new patent applications. All specifications include school fixed effects and school-specific time trends. Standard errors are clustered at the school level. The last row reports the first stage F-statistic for the instrument.

6.3. Licensing

The more fundamental question underlying these results is whether the pool of knowledge generated by research support expenditures actually creates valuable technology. We take a revealed preference approach, i.e. we use the fact that a straightforward lower bound for value is what unaffiliated, private-sector firms are willing to pay for these innovations. These amounts are reflected in university technology licensing revenue. The measure is salient to decision-makers. Jensen and Thursby (2001) show that both university administrators and technology transfer office employees rank licensing revenue as the most important outcome of their work (compared to the number of agreements executed, inventions commercialized, sponsored research, and patents awarded).[56]

Table 5 reports estimates from Eq. (4) when output is measured in log licensing revenues. We find an elasticity with respect to institutional research support of 1.86. Similar point estimates and standard errors are arrived at when we winsorize outcomes at the 2.5% and 5% level, which indicates outliers do not drive these results. The F-statistic on the excluded instrument is 14, 20–30% lower than that reported in the prior tables, reflecting some missing right-hand side values that preclude certain observations from entering the first stage estimating equation. As in the prior two tables, IV estimates exceed OLS counterparts. Related to this fact, coefficients on faculty salaries and facility expenditures are not statistically separate from zero.

Though they exceed one, we interpret coefficients reported in the top row as indicative of approximately constant returns to scale, which is within a standard error of our point estimates. Scale economies are unlikely in this setting, especially at the level of the institution, except under extreme circumstances. In either case, the analysis indicates meaningful returns on marginal expenditures for the university. These estimates indicate that schools earn between 5 and 11 cents of upfront licensing revenue on every dollar of research expenditures at the margin.[57] Moreover, since licensing revenue involves streams of recurring payments, evidenced by the fact that total licensing revenues average more than three times upfront licensing revenues, university may earn up to between 15 and 35 cents back on each dollar of research support at the margin. This comes in addition to other non-pecuniary benefits, e.g. added prestige through discovering and publicizing new findings, as well as social benefits, e.g. those derived from spillovers. Together these figures tend to reject the claims of STEM funding critics who argue that real returns are low at the margin.

6.4. Timing of output

To assess the assumptions on timing underlying Tables 3–5 and to address concerns about intertemporal substitution, we re-estimate our main specifications but replace our right-hand side measures with ones that are lagged one less year as well as one, two, and three additional years. The appendix reports the results from this exercise. Coefficients from the lag structure in our main specifications are much larger than—often by an order of magnitude—coefficients from alternate specifications. Whereas each of the three former coefficients are significant at the 95% level, only one of the twelve latter coefficients are significant at even the 90% level. Taken together, these results support the notion that our main specifications capture the important effects of research support on scientific output. Moreover, while they cannot completely mitigate concerns that current expenditures merely draw forward from the future many discoveries that would have occurred anyway, these results suggest that any intertemporal substitution that does occur tends to cancel out against discoveries that occur subsequent to the narrow window we consider.

These lags reflect several factors beyond the mere speed of STEM research. First, faculty are encouraged to protect their ideas as soon as laboratory results provide proof of concept. Doing so ahead of any seminars, conference proceedings, and working papers limits subsequent, costly disputes over IP ownership. As Virginia Tech advises its scholars, "if you are going to publish or present your idea … let us know in advance. We can file a provisional application to keep the idea protected."

Second, the resulting provision filings are cheap and fast to write and submit. As particularly extraordinary evidence of this, several patent applications that both relate to airline security and explicitly reference the September 11, 2001 terrorist attacks were filed within days of the incident. At least one was filed on the day of the attack.[58] Another was filed by Honeywell on the following day.[59]

Third, these filings prompt TTO staff, third-party brokers, and even experienced faculty to contact potential licensors. As Stanford's

[56] Faculty ranks it second only to sponsored research, although this gap has likely dissipated since their survey was administered in the late-1990s.

[57] To arrive at the first figure, we rely on an elasticity of 1.43, the midpoint between 1.0, i.e. constant returns to scale, and 1.86, the estimate in the first row, final column of Table 5. We multiply this by the ratio of average upfront licensing revenues to average institutional research support in the final year of the panel. To arrive at the second figure, we re-estimate the main specification in terms of levels rather than in logs.

[58] See US provisional application no. 60/322,197 titled "Aircraft flight security system and method," which has priority date September 11, 2001.

[59] See US provision application no. 60/318,984, titled "Emergency Flight Control System," which has priority date September 12, 2001.

Table 5
Licensing estimates.

Variables	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Institutional research support [$\tau - 1$]	−0.038	0.00839	0.0673	1.94**	1.93**	1.86**
	(0.168)	(0.168)	(0.175)	(0.945)	(0.98)	(0.938)
Facility expenditures [$\tau - 1$]	−0.00862	−0.00093	−0.0133	0.0318	0.0385	0.0234
	(0.234)	(0.243)	(0.251)	(0.346)	(0.349)	(0.345)
Faculty salaries [$\tau - 1$]	−0.0599	−0.0618	−0.0839	−1	−0.984	−0.941
	(0.735)	(0.767)	(0.792)	(10.06)	(10.09)	(10.09)
Observations	919	919	919	919	919	919
R-squared	0.752	0.755	0.752	0.679	0.692	0.701
Winsorized pct.	5	2.5	–	5	2.5	–
F-Stat: 1st Stage	–	–	–	14.23	14.23	14.23

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
The right-hand side variables are the logs of faculty salaries, facility expenditures, and institutional research support, the last of which takes predicted values in columns 4-6. The left-hand side variable is the log of licensing revenues. All specifications include school fixed effects and school-specific time trends. Standard errors are clustered at the school level. The last row reports the first stage F-statistic for the instrument.

Office of Technology Development states, "concurrently with making the patent decision, [a Licensing Associate] will market and, if successful, begin licensing negotiations with potential licensees." In many cases, the licensing process can precede intellectual property disclosures. As Stanford's office goes on to state, "it is desirable to have an interested potential licensees [sic] before committing to patent filing."[60] These statements are broadly consistent with our conversations with TTO officers[61] as well as findings in Jensen and Thursby (2001). When they asked TTOs what stage inventions were in when they were licensed, 48% replied "proof of concept but no prototype" while 29% replied "prototype available but only at lab scale."

Fourth, publishing research in the STEM fields is relatively fast. Manuscript submission-to-acceptance times are measured in days or weeks rather than months or years, and faculty frequently rely on short papers, proceedings, and letters to disseminate their work. As an example, the main journals of the American Physics Society boast median submission-to-acceptance times less than eighty days, and their "Rapid Communication" section offers times less than fifty.[62] Editors of *Physical Review B*, which covers condensed matter and materials physics, state, "in rapidly developing fields editors have accelerated peer review and accepted papers in as little as a week. We invite our authors to request such expedited handling at the submittal stage."

To assess the plausibility of these lags with external empirical evidence, we collect data measuring lags between federal research grants and subsequent patenting and publishing. We restrict ourselves to grants awarded by the major NSF STEM programs, i.e. those in nuclear physics, particular/atomic physics, probability/statistics, mathematics and computer science, astronomy and astrophysics and other physics, chemistry, and biology, which maintains comparability with prior figures. In the appendix, we plot the distribution of these lags across awards. The modal time from award to patent application is twelve to eighteen months and from award to publication is twelve months after that. These correspond to the lags considered in our main patent-based and publication-based specifications, respectively. Skew in both distributions pushes the average lags out about ten to twelve months in both cases, so observed lags on federal research grants are slightly longer than what we observe among institutional research support. However, these differences may reflect the fact that, for example, the latter target projects that are "shovel ready."

To explore whether STEM research is especially "fast," at least relative to what many readers are familiar with, we also gather data measuring publication lags in the social sciences. We consider grants awarded by NSF programs in economics, linguistics, management, law, and anthropology, and we combine this data with that described in the preceding paragraph. In the appendix, we plot the average lag by NSF program, which reveals substantial heterogeneity. Each of the social science fields face longer lags than any of the STEM ones. As one particularly striking example, average lags are under one year in nuclear and particle/atomic physics — half the length of those observed in economics and in law.

6.5. Bounds on long run effects

The underlying budget variation derived from football has two features that require discussion of how externally valid, i.e. policy relevant, our results are. First, the underlying shocks are treated as temporary. In theory, the university could take its unexpected surplus and make long term investments (e.g., a faculty member or construction project). Absent organizational constraints and behavioral reasons, they may. Nonetheless, they do not. Second, the underlying shocks are roughly zero sum on average. If one school exceeds expectations, then some other school falls short by about the same amount. Thus, while our instrument measures the impact of temporary budget shocks that are zero sum across schools, the policy-relevant budget shocks would likely be permanent or aggregate or, more likely, both.

For a temporary shift of internally provided research expenditures, the results are very informative. Administrators should treat those budget changes similarly to those generated by the instrument and confine themselves to adjusting research support. Whether the shift is an idiosyncratic or aggregate one is unlikely to matter, since research support is relatively elastically supplied in the short run. For example, software can be replicated very quickly, and bacteria and mice nearly as quickly.

For a permanent shift, the answer is more complicated. Universities may choose to poach faculty or undertake capital projects, which is problematic in light of Goolsbee (1998a,b). These papers showed that while the intention of federal R&D subsidies and investment tax credits is to boost research and investment activity, respectively, the inelasticity of the supply of these inputs means that price increases

[60] "Technology Licensing and the Patenting Process at Stanford." Stanford Office of Technology Licensing. https://web.archive.org/web/19991007204023/http://www.stanford.edu/group/OTL/patentprocess.html (accessed September 11, 2016).
[61] For example, one administrator from a Top 10 research institution stated, "[the] majority of technologies are licensed before patents are granted — often companies license the technology just on the provisional patent application." This is particularly informative because provisional applications are in force for at most twelve months.
[62] Compare with the *American Economic Review*, where this time averages 62 weeks (using 2008 data) (Moffitt, 2009).

can absorb a large portion of government expenditures. The latter of these papers finds, for example, that 30–50% of additional federal research expenditures may go towards private sector scientist and engineering wages. However, Goolsbee focuses on short and medium run effects because the policies studied are aimed at troughs in activity at weak points in the business cycle. Since faculty require three to six years of PhD or PhD-equivalent training, depending on discipline, they will be supplied at least as inelastically as their private sector counterparts, suggesting we overstate the returns to a policy change. However, permanent shifts may create long run impacts. Over this horizon, faculty and facilities can adjust. By the envelope theorem, our results likely provide a *lower bound* for the policy-relevant parameters.

6.6. Bounds on input measurement error

The ratios of OLS to IV estimates suggest an errors-in-variables problem. With additional restrictions, it is possible to estimate—or at least bound—the variation attributable to measurement error. To do so, define residuals from true and observed research support such that $m' = m - \mathbb{E}[m|W,\tilde{l},\tilde{k}]$ and $\tilde{m}' = \tilde{m} - \mathbb{E}[\tilde{m}|W,\tilde{l},\tilde{k}]$, respectively. Also, define θ^{OLS} as the ordinarily least squares analog of θ in Eq. (4), i.e. the coefficient that would be obtained were $\hat{m}$ replaced with $\tilde{m}$. If, for simplicity, we assume that ϵ enters Eq. (3) linearly with coefficient ξ but does not determine l or k,[63] then $\mathbb{E}[\theta^{OLS}] = \beta_m \frac{\sigma^2_{m'}}{\sigma^2_{m'}+\sigma^2_e} + \xi \frac{\sigma^2_{\epsilon}}{\sigma^2_{m'}+\sigma^2_e}$. The first term represents downward bias from right-hand side measurement error while the second represents bias from ϵ partly determining m.

Re-arranging terms yields that the proportion of *residual* ("within") variation in observed expenditures attributable to measurement error is bounded such that

$$\frac{\sigma^2_e}{\sigma^2_{m'}+\sigma^2_e} = 1 - \frac{\mathbb{E}[\theta^{OLS}] + \xi\frac{\sigma^2_{\epsilon}}{\sigma^2_{m'}+\sigma^2_e}}{\mathbb{E}[\beta_m]} \geq 1 - \frac{\mathbb{E}[\theta^{OLS}]}{\mathbb{E}[\beta_m]}. \tag{5}$$

The inequality follows directly from the fact that ξ and $\frac{\sigma^2_{\epsilon}}{\sigma^2_{\tilde{m}'}+\sigma^2_e}$ are both weakly positive. Moreover, multiplying this bound by $\frac{\sigma^2_{\tilde{m}}}{\sigma^2_{\tilde{m}'}}$ yields a bound on the proportion of *total* variation in observed expenditures attributable to measurement error. To approximate these bounds, we replace $\mathbb{E}[\theta^{OLS}]$, $\mathbb{E}[\theta]$, $\sigma^2_{\tilde{m}}$, and $\sigma^2_{\tilde{m}'}$ with their sample analogs. This approach indicates that measurement error in research support accounts for at least 19.3–21.6% of *total* variation and at least 79.5–80.1% of *residual* variation.[64]

What contributes to such high figures in our setting? First, since the NSF expenditure categorizations differ from financial reporting standards, the data cannot excerpt from audited statements. The NSF asks for only science and engineering research expenditures whereas the universities publicly report total research expenditures, so even "top line" expenditures figures may require a judgment call on behalf of the respondent. This problem surely worsens as the survey questions become more detailed (e.g., require discipline-level expenditures by source). It was apparent from the data that the demarcation between biology and medicine is particularly difficult for respondents to make.[65] It was also apparent that this demarcation shifted at times within the institution.[66]

Second, although there is a large penalty for not returning the survey, there is little harm in making mistakes. In some cases, we spotted obvious errors in expenditure figures. To the credit of the NSF staff, when we followed up with them, it was clear they were aware of the mistakes and often had already queried the schools about them, which suggests that the errors we observe were those simply too difficult to resolve. On the one hand, cost accounting is hard and time consuming, so expecting a painstaking "re-audit" of a large portion of outgoing university cash flows is clearly too much to ask. On the other hand, as we have shown, errors can badly bias the estimates of research productivity that rely on them, shifting public policy in undesirable ways. This raises questions about the degree to which other heavily relied upon survey instruments suffer from this problem (e.g. the US Census Annual Survey of Manufacturers), and whether incentives for accurate reporting are large enough for "high stakes" policymaking.[67]

What contributes to the sharp differences among the figures? Simply put, budgets vary systematically across schools but grow predictably over time. Fixed effects, for example, sweep away the large persistent expenditure differences between, for example, the University of Michigan and the University of Miami. The inclusion of school-specific trends strips out even more variation. Much of what remains—at least leaving aside the unexpected shocks that, for example, surprise athletic wins and losses provide—is noise.

7. Conclusion

Unanticipated college football outcomes shift institutional research support but not expenditures on faculty or facilities. Since they are unlikely to otherwise impact research productivity *and* are uncorrelated with right-hand side measurement error, these shifts provide helpful variation to identify the impact of money on science. We use this variation to measure the dollar elasticity of scholarly articles published and new patent applications filed. We also use this variation alongside data on university technology licensing revenues to provide the direct evidence that the pool of knowledge created by academic research, at the intensive margin, generates valuable technology.

The findings highlight the need for additional work to guide policy in this area, particularly in determining how production inputs are measured and non-licensing output should be valued, which entities best allocate expenditures, and what individual or institutional circumstances generate high returns on those expenditures.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jpubeco.2019.104066.

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[63] Put differently, $\eta = \xi\epsilon + \nu$, where ν is i.i.d. noise.

[64] The bottom and top endpoints of the ranges are based on coefficients obtained in columns 4 and 8 of Table 3 and columns 3 and 6 of Table 4 and the variance in the 1071 and 1108 observed values of institutional research support, respectively. The licensing-based coefficients are estimated with considerably more error; these would have provided 50.1% for the proportion of total variation and 93.6% for the proportion of residual variation.

[65] These demarcations appear to reflect geographic idiosyncrasies of the campus, i.e. determined by what proportion of biology equipment or staff housed within medical center facilities.

[66] According to an NSF survey statistician, this probably reflects changes in which university staff were filling out the NSF form.

[67] In a way, this is precisely what a data initiative such as UMETRICS, described in Section 4, is addressing.

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