THE IMPACT OF MONEY ON SCIENCE: EVIDENCE FROM UNEXPECTED NCAA FOOTBALL OUTCOMES*

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Abstract

Scientific discovery drives economic growth, but the high cost of research makes funding a limiting factor. Little is known about the causal impact of money on science, despite its importance for determining the socially-optimal level of R&D. This paper estimates the dollar elasticity of research output at American universities by using unexpected NCAA football outcomes to exogenously shift research budgets across schools and time. After constructing an original dataset of historic team success, measured by vote tallies from the Associated Press Top 25 Poll, we show that unexpected within-season changes to this measure are strong predictors of non-federally-sponsored research expenditures at the school in the subsequent year. These changes do not predict federally-sponsored research expenditures, lending further support for the instrument. The estimated dollar elasticities are 0.31 and 0.59 when the output measures are scholarly articles and their accrued citations, and are 1.91 and 3.30 when the output measures are new patent applications and their accrued citations, respectively. It costs the university, at the margin, about $2.61 million to generate a patentable idea. For each measure, the instrumental variable results contrast sharply with OLS estimates, which are near zero and could lead policymakers to under-invest in research. JEL (I23, I28, O31, O32, O38)

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Investments in science can generate large social returns. Scientific discoveries have eradicated diseases, reduced famine, increased labor productivity, and supported national defense. However, scientific laboratories and experiments are expensive to run and research funds are often the key limiting factor in scientific advancement. Together these facts make the level of R&D investment a central concern of university administrators and public policymakers. There is urgency about this issue in the United States where the federally-financed share of university research has fallen over the last forty years and recent recession-induced budget cuts have slashed states' investment in academic research. These developments prompted the America COMPETES Acts of 2007 and 2010 [National Research Council, 2012], which called for a doubling of funds to basic science, and a potential reauthorization of the Act in 2014. Despite its salience, the question of whether policymakers fund a socially-optimal level of R&D remains open, largely because there are few estimates of the causal impact of research expenditures on scientific discovery.

This paper estimates the dollar elasticity of research output across American universities. It addresses two empirical challenges. First, research grants tend to be awarded to more productive institutions. This endogeneity causes parameter estimates to be upward biased. Second, expenditure data that includes long-term projects of various lengths and lags will make tying money to outcomes difficult. For example, construction of the multi-billion dollar Large Hadron Collider began ten years prior to the first experiments. This errors-in-variables problem causes estimates to be downward biased. The first of these problems suggests—at a minimum—controlling for institution-specific effects, although this tends to amplify the bias from the second. To solve both problems, we exploit an exogenous shifter of marginal research funds between universities: the unexpected success of college football teams.

Identification relies on the fact that football team performance impacts 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 *unanticipated within-season* changes to team success. We measure football team success using the Associated Press Top 25 Poll and use the difference between post-season and pre-season vote counts as the instrumental variable. Since the individual voting results of the Top 25 Poll are made public, and the professional sportswriters who vote have a significant reputational stake in properly forecasting teams' quality and teams' true prospects, the difference between post-season outcomes and pre-season expectations can be treated as random.[1]

Three aspects of this relationship aid greatly in obtaining results. The first is the degree to which swings in football fortunes impact overall school finances. Since the late 1980s college football has generated tens of billions in cash flow to American colleges and universities. One of the more prominent examples is the University of Texas at Austin: in 2013 its football team generated more revenue than the majority of

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

professional National Hockey League teams.[2]

At Louisiana State University, football revenue is nearly a third of total tuition receipts. A large portion of this revenue is ploughed back into the athletic department, but a sizable part is returned to the school's general account in the form of unrestricted funds. In addition, a successful football season on the field usually translates to a successful fundraising campaign off the field. For example, Texas A&M University raised more money the night after its star quarterback Johnny Manziel's Heisman Trophy win than it typically raises in a month, in turn setting records for quarterly and annual alumni giving. The second is that this source of funds is highly volatile, which means that administrators are likely to treat these changes as temporary windfalls rather than opportunities to start long-term projects. The third is that much of a team's success is, in fact, quite unpredictable. This is empirically true in our data and a fact to which college football fans can attest.

We use a two-stage least squares (2SLS) specification to estimate the impact of money on scientific output, which we measure in four ways. When the output measures are scholarly articles and the citations that accrue to them, we estimate dollar elasticities of 0.31 and 0.59, respectively. When the output measures are new patent applications and the citations that accrue to them, we estimate dollar elasticities of 1.91 and 3.30, respectively. These estimates contrast sharply with non-IV estimates under the same specification, which tended toward zero. All calculations are made controlling for time and school effects and school-specific time trends. The non-IV results closely resemble prior work by Adams and Griliches [1996, 1998] and would lead to underinvestment in scientific research, with two important caveats as these results apply to policy-setting. First, since the predicted variation in research expenditures is linear in the instrument, unexpected losses hurt research budgets as much as unexpected wins help them. The transfers of research funds between schools are assumed to be zero sum. Consequently, if the schools happen to be merely trading scarce output-producing assets—like highly productive scientists—then an aggregate increase in research expenditures might have no impact at all, even though our results predict a strong positive impact of expenditures on each *individual* institution. This seems unlikely, since small and perhaps temporary budget shocks are unlikely to result in long-term and expensive commitments like hiring. Moreover, these high output faculty would bring federal grants along with them, a point we address below and do not see in the data. Delineation of exact mechanisms that govern research-fund allocation processes within universities is beyond the scope of this paper. Nonetheless, this is an important question we leave for future research. Second, the main specification relies on a set of important assumptions about the timing of football success, research funding, and scientific publishing. Misspecification can bias the coefficients, so

[2]Smith, Chris. "College Football's Most Valuable Teams 2013: Texas Longhorns Can't Be Stopped." Forbes, December 18, 2013. http://www.forbes.com/sites/chrissmith/2013/12/18/college-footballs-most-valuable-teams-2013-texas-longhorns-cant-be-stopped (accessed December 2, 2014).

we provide support for our assumptions and discuss the factors underlying the temporal relationships.

Figures 1-2 illustrate the reduced-form relationship. The x-axis in each shows unanticipated football success, measured by within-season changes in Associated Press voting. In Figure 1, the y-axis in the top panel represents the log of the count of scholarly articles published and in the bottom panel represents the log of the count of the citations that accrue to those articles. In Figure 2, the y-axis in the top panel represents the log of the count of new patent applications and in the bottom panel represents the log of the count of the citations that accrue to those applications. We remove school and year fixed effects as well as school-specific time trends from the variables on both axes. The x-axis has been standardized across polls by standard deviation and lagged appropriately. The positive impact of unexpected football outcomes on all four measures of scientific discovery are positive (and significant at 95%).

[Figure 1 about here.]

[Figure 2 about here.]

[Figure 3 about here.]

[Figure 4 about here.]

We can strengthen the causal interpretation of this relationship with an exogeneity check. Since we observed research funding from federal and non-federal sources separately, we can assess the impact of unexpected football outcomes on both independently. Of course while research funding coming from non-federal sources should be affected by football, those coming from federal sources should not. We find strong evidence for this fact in the data.

This paper contributes to several literatures. In measuring the elasticity of university research expenditures, it follows closely in the footsteps of Adams and Griliches [1996, 1998]. Their cross-sectional OLS specification combines observations over their panel and finds a dollar elasticity of 0.5 when the outcome measure is the number of scholarly articles and 0.6 when the outcome measure is the number of citations that accrue to them. However, when they include university fixed effects to control for institution-specific unobservables, elasticities fall by 80% and are no longer separate from zero. They conclude, *"To date we have little hold over changes in financial and other circumstances that bring about a change in the stream of a university's research output."* This is precisely the issue we wish to address.

The scope of our study extends beyond scientific publishing to patenting behavior. After the passage of the Bayh-Dole Act in 1980 allowed academic institutions to retain ownership of inventions developed through federally funded research, it incited a strong growth in academic patenting and patent licensing

[Henderson et al., 1998, Sampat et al., 2003, Hausman, 2013]. Pakes and Griliches [1980, 1984] were first to consider patents as an outcome of interest. They found a positive relationship with lagged investment and knowledge stocks in firms.[3] Relatedly, Azoulay et al. [2014] study the impact of government research grants on private sector pharmaceutical and biotech firms. They exploit institutional features of the granting institution to address endogeneity issues and find that a $10 million increase in government funding generates 3.3 additional patents. Jaffe [1989] spawned a related stream of papers that measured whether R&D efforts spillover to local private firms. The focus on spillovers, however, led this paper and those that followed to focus on exogenous shifts to university research activity rather than university research spending *per se*. As an example, Hausman [2013] uses the Bayh-Dole Act to credibly demonstrate these spillovers on a host of private-sector outcomes like profits and employment. In addition, we shed more light on the mechanisms utilized by academic institutions to fund scientific R&D. The roles of government [Nelson, 1959, Jaffe, 1989, Henderson et al., 1998] and private industry [Mowery and Rosenberg, 1989, Cohen et al., 1998, Wright et al., 2014] have been extensively studied, while the role of science philanthropy only recently started to attract more attention [Murray, 2013].

This paper also contributes to recent literature using athletic outcomes for identification. Card and Dahl [2011], for example, study how external cues precipitate violence by showing that domestic abuse rises in cities where the local NFL team suffers an unexpected loss. Anderson [2012] asks whether schools are justified in their large investments into college sports and uses the difference between realized outcomes and betting spreads to show that winning attracts students and donations. Meer [2013] tests habit formation in charitable giving by using prior years' athletic success as an instrument for past giving. The tie between athletics and donations was established previously in Meer and Rosen [2009] using university microdata.

1 US College and University Research

Spending Levels

Colleges and universities conduct more than 15% of total research and development in the United States, which totaled $450 billion in 2013. They also account for more than 50% of basic science expenditures [Battelle Memorial Institute, 2013]. These institutions historically relied heavily on the federal government for funding, although the federally-funded share of research has fallen from 78% to 67% over the past four decades. Private funding from corporations has stayed essentially flat, despite wide year-to-year variation. Institutionally-sourced funds have partially compensated, rising from 11% to almost 20% over the same

[3]See Griliches et al. [1988] for a survey of the early literature.

period [National Science Foundation, 2013]. Survey data also suggests this increase is insufficient: 84% of US academic researchers expressed concern over the reduction in US federal R&D funding. For comparison, consider the following: despite the widely publicized shortage of qualified R&D staff in the United States, only 48% of researchers listed this issue as a concern [National Research Council, 2012].

Congress and the White House have taken notice and begun to act on these concerns. In 2005, Congress asked the National Research Council to prepare a plan that would ensure American competitiveness in science and technology. Congress then provided bipartisan support for the America COMPETES Act, which President Bush signed into law in 2007. The Act emphasizes investment in the science, technology, engineering, and mathematics fields and authorizes a doubling of National Science Foundation (NSF) grants for many fields by 2011. In 2009, Congress requested a follow-up report. Two years later, President Obama signed a reauthorization of the bill, the America COMPETES Act of 2010. The budget sequestration process of 2013 reignited this debate. Ultimately, the authorized funding increases were not realized. This has prompted the Director of the National Institute of Health to worry that "we will lose a generation of young scientists" and that "a lot of good science just won't be done."[4]

As of the time of writing, Congress has proposed but not yet passed another reauthorization of the Act. A central driver of this debate is uncertainty about where the funding level stands in relation to the optimal social level of R&D, which itself turns on the underlying return on research investment. Measuring this return requires a more detailed examination of the funding process.

1.1 How Research is Funded

Private colleges and universities fund their operations primarily through tuition, federal grants, philanthropic donations, and auxiliary enterprises (like healthcare and athletics). For public universities, state appropriations also account for a significant share of incoming cash flow. Schools then use these funds mainly for student instruction, research, administration, and running the auxiliary programs. They budget operational expenses on an annual basis[5] and typically follow a June rather than December fiscal year end to synchronize with the course-year calendar.[6] The unused portion of funds are rarely allowed to carry over to the next year (Porter, pers. comm., July 22, 2014).

The budgeting process is complicated by widespread earmarks. Strict guidelines on how funds can be spent are attached to a large portion of incoming cash flow, creating a distinction between "restricted"

[4] Vergano, Dan. "Science Faces Sequestration Cuts." USAToday, February 25, 2013. http://www.usatoday.com/story/tech/sciencefair/2013/02/25/budget-nih-collins/1947277/ (accessed December 2, 2014).

[5] We use the word "operational" to separate these from capital expenses, like construction projects, which are likely to be budgeted long ahead of time.

[6] There are a few exceptions to the June fiscal year end but these too end in the summer months and are immaterial for our discussion.

and “unrestricted funds.”[7] Some earmarks are obvious: an NSF grant will go directly to the project for which it was awarded and state appropriations will directly subsidize instruction of in-state residents. Other earmarks are not so straightforward. A multi-million dollar donation by a wealthy single donor or a foundation could carry with it the requirement that it be used to extend hours at an art museum or gymnasium, increase a particular genre of books in the library, or expand the student center. For example, in 2010 Harvard University received a restricted gift of $50 million from the Tata family to fund two new buildings on the business school campus.[8] For both bookkeeping and flexibility reasons, these unrestricted funds are a precious commodity.

For research, unrestricted funds are often the “source of last resort.” They are needed when costs run over, other sources fall short, or faculty are too new to have attracted sufficient grant money. That is, although federal and state funds still account for the majority of university-led R&D, they are frequently too slow or inflexible to handle the immediate and diverse needs of academic scholars. In the absence of unrestricted funds to close the gap, research is often put on hold. Murray [2013] identifies philanthropic donations as one possible channel for research institutions to fill funding gaps and provides a great example: in 2008, when the fiscal crisis forced the State of California to reduce funding to the UC Berkeley’s Radio Astronomy Lab and federal government cut funding for Allen Telescope Array, Microsoft’s Paul Allen stepped in and donated funds to ensure continuous operation of the facility.[9] Combined with other, both large and small philanthropic gifts, unrestricted funds can also allow for scientific research to continue when federal financial support for science does not deliver. Other sources of unrestricted funds include auxiliary operations, like athletics and healthcare, housing, and tuition (primarily for out-of-state residents in the case of public schools). Since it enables us to identify and precisely estimate the elasticity of research output, football’s contribution is covered in detail below.

How Football Contributes Financially

> “We took direct dollars from the athletic budget and put it into academic programs.”
>
> E. Gordon Gee, 11th and 14th President, Ohio State University[10]

[7] We thank Kyle Welch for bringing this to our attention.

[8] Walsh, Coleen. “Business School Announces Tata Gift; Two Initiatives.” Harvard Gazette, October 14, 2010. http://news.harvard.edu/gazette/story/2010/10/hbs_gift/ (accessed December 2, 2014).

[9] Murray [2013] emphasizes three key points about science philanthropy: that it is mostly channeled into restricted funds, that it heavily favors translational science, and that it generally does not strive to fill funding gaps. However, it is important to note that her study focuses on large philanthropic gifts (>$1M) at top 50 research institutions and provides only one part of the funding equation. Some of these large philanthropic gifts happen to be unrestricted, and universities also collect many small philanthropic gifts which are usually unrestricted in nature. For example, the Harvard Alumni Association webpage provides opportunities for alumni to donate directly to the various university funds, most of which are unrestricted.

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

Football contributes to unrestricted university finances in two ways. The first channel is auxiliary revenues. Since the late 1980s, Division I NCAA football has generated over $10 billion in sales. For perspective, Table 1 provides the top 20 college football teams in terms of revenue. The sheer size of these programs is staggering, especially in relation to professional teams. For example, The University of Texas at Austin earns nearly $110 million in revenue. For comparison, this figure is 40% higher than the median professional hockey team and on par with the median professional basketball team. On a per game basis, it is 5 times larger than both of these and about 7 times larger than the median baseball team. Their size relative to total tuition is also quite large. More than half of the schools on the list have football programs that are more than 20% of the total tuition receipts. At Louisiana State University and Agricultural and Mechanical College (LSU), the University of Nebraska-Lincoln, and the University of Oklahoma Norman Campus, this figure is nearly a third. Football also dwarfs other athletics in this sample. With only three exceptions, football contributes more to athletics revenue than all other sports combined. This is generally true outside of the current sample, too. Despite the popularity of college basketball, for example, its financial importance pales in comparison to football across virtually all US schools.

[Table 1 about here.]

A share of these revenues 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 post-season bowl winnings to fund academic priorities. From 2011 to 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 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].

The second channel is alumni contributions. Football success is a major catlyst for philanthropic fundraising shocks [Meer and Rosen, 2009, Anderson, 2012]. 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 (Porter, pers. comm., July 22, 2014). 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".[11] Schools also can directly tie athletic privileges to academic donations. Stinson and Howard [2010, 2014] document how one large Midwestern school makes donors of academic

[11] 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).

gifts over $3,000 eligible to buy season tickets.

Football success, and most likely its financial contribution, are quite volatile. This is shown in the right-most two columns of Table I. Sixteen of the twenty schools have competed for the national championship over the panel 1987 to 2012. On the other hand, every team was unranked at least twice over the panel, and many were unranked more than ten times. These reversals of fortune are important because variation in teams' rank provides the underlying variation for our identification. For example, a surprising 11-0 record of Boise State University football team in 2004-2005 resulted in an marked increase in university donations, a 66% increase in sales of university merchandise at the bookstore, and a 60% increase in sales of the subsequent year's seasons tickets [Grant et al., 2008].

2 Data

2.1 Sources

We draw data from four sources. The first is vote data from the Associated Press (AP) Top 25 Poll, which we use to construct our instrumental variable. The poll surveys sixty-five sportswriters and sports broadcasters. Each provides a ranking for the top twenty-five teams from NCAA 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.[12] The AP publishes the vote totals of all 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 pre-season votes from end-of-season 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 has 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 NCAA football champion until 2013.[13] At least three other polls are widely published, although the AP Poll is the best known. Moreover, although they are closely correlated, the other major polls had obvious limitations for our setting.[14] 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.

The second component is academic publishing data. Thomson Reuters Web of Science collects this for

[12]The exception is for 1987 and 1988, where 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.

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

[14]The BCS Poll, for example, did not cover our full sample. The Coaches Poll could, hypothetically, be contaminated by strategic voting. Other polls were much less widely known and relied upon.

their Incites database product. We extract a count of the scholarly articles published and a count of the citations that accrue to those articles (up to the date of data retrieval). Observations are specific to a calendar year, institution, and academic discipline. Since the instrument only has variation at the institution-year level, we aggregate up to this level by taking a sum over all science disciplines, excluding social sciences and medicine.[15] Although including the latter two categories improves power in our first stage, it can bias our estimates away from the elasticities of interest.[16]

The third component is US patent application data. Thomson Reuters collects this for their Thomson Innovation database. It allows us to identify university patentees better than the raw USPTO patent records. We use the browse feature in Thomson Innovation Assignee/Applicant search field to identify all possible university name variations together with unique 4-letter Assignee Codes identifying one of approximately 22,300 patenting organizations worldwide. This enables us to count and aggregate patent applications wherever a college or university appears as an assignee or applicant on the patent record. Again, we extract a count of new patent applications filed and a count of the citations that accrue to those patents (up to the date of data retrieval). Although patents are assigned into technological classes, there is no clear map to academic disciplines. Thus, we aggregate up to the institution-year level by taking a sum over all classes. We assemble this data on a fiscal year basis. More details on patent dataset construction are provided in the Appendix.

The final component is university research expenditure data. The National Science Foundation (NSF) collects this data annually in their Higher Education Research and Development Survey (prior to 2010, called the Survey of R&D Expenditures at Universities and Colleges). Responses are carefully reviewed and verified as needed.[17] The survey is an annual census of all institutions spending at least $150,000 in separately budgeted R&D. The data is broken down by federal and non-federal sources as well as by disciplines. Our first expenditure measure is tied to scholarly articles, so as with the Thomson Incites data, we take a sum over all science disciplines, excluding social sciences and medicine.[18] Our second expenditure measure is tied to new patent application filings, which are not discipline specific, so we take a

[15]For the Incites database, this includes physics, chemistry, mathematics, computer science, biology and biochemistry, microbiology, plant and animal science, agricultural science, geoscience, environmental science, and ecology.

[16]Social sciences are not central to the current policy debate. They also tend to have longer and more dispersed publication lags relative to non-social sciences, which will bias our coefficient estimates downward (unless we take a much stronger stand on the timing). In the same vein, medical research will include a large number of development applications relative to the other natural sciences. Unrelated to these, we are also forced to exclude space science, which includes astronomy but is dominated by aerospace and aeronautical engineering.

[17]In two cases where we needed clarification, the NSF had also asked for them. This gave us confidence that the data was thoroughly reviewed and validated by the NSF. Ronda Britt at the National Center for Science and Engineering Statistics was particularly helpful. Our main issue was missing values for Boise State University prior to 1992 and in 2005 and 2006. In the earlier years, the institution was below the survey threshold. For the later two years, the NSF followed up with the school and confirmed it made an error in reporting due to a personnel change. We omit these years from our analysis, although the results are robust to dropping this institution entirely.

[18]For the NSF data, this includes physics, chemistry, and mathematics and statistics, computer science, biological sciences, and other life sciences, agricultural sciences, geosciences, oceanography, atmospheric sciences, and earth sciences.

sum over all non-social science, engineering, and medical disciplines. This data is on a fiscal year basis.[19]

Panel Length and Scope

The instrument is based on the difference between post-season and pre-season votes. Since the median NCAA team receives zero votes, using the universe of teams would result in a very large number of zero values. So that the schools are selected agnostically and the instrument has power, we simply order the teams by the sum of the absolute value of their vote changes and select the top forty schools for our panel. This is exactly $\frac{1}{3}$ of the 120 Division I teams. The only caveat is that if there are heterogeneous treatment effects, our estimates pertain only to schools with large football programs. The resulting list is very diverse. It includes private (e.g. Stanford, Notre Dame) and public (e.g. Alabama, Nebraska) institutions as well as relatively small (e.g. Boise State) and large (e.g. Texas) ones. The magnitude of our estimates are not very sensitive to the size of the panel.[20]

The beginning of the panel coincides with the start of the "modern era" of college football, which traces back to the 1984 Supreme Court ruling on *NCAA v. Board of Regents of the University of Oklahoma*.[21] Prior to the ruling, the NCAA restricted the number of games that could be broadcast, threatening non-complying schools with an association-wide boycott. In 1981, two schools challenged the NCAA's authority and in 1984, the Burger court ruled that the NCAA violated antitrust laws by controlling television broadcasting rights. Effectively, schools and their conferences were now 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 an unprecedented financial gain. That year featured the highly contentious Fiesta Bowl, which became one of the most watched college games in history, and marks the start of our panel of football outcomes.[22] Data on scholarly articles begin on the same date, while the patent data begin in 1996. Although we observe data for earlier periods, the international harmonization of the Unites States patent system in the early 1990's created a large spike in the number of filings and seemingly increased the overall level of patenting. If the response of patenting behavior to research funding was different prior to 1996, and the goal is to recover parameter estimates

[19]This includes all departments from the first measure, as well as medical sciences (including clinical medicine, immunology, pharmacology and toxicology, and molecular biology), engineering (including aerospace, chemical, civil, electrical, materials, mechanical, and other), interdisciplinary and other sciences, and astronomy (which, along with aerospace engineering, would be classified as "space science" in the Incites database).

[20]Clearly, however, shrinking the list far below forty simply limits power throughout specifications while expanding the list far beyond forty can introduce enough zeros to the instrument to weaken it.

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

[22]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. The national press coverage of the players, coaches, their backgrounds, and the developments leading up the game are all common in the "modern era" but were unheard of prior to 1987.

that are informative for current policymaking, then including data on filings prior to 1996 will lead to the wrong parameter estimates. The dataset ends in 2011. While 2012 data was available for our outcome measures, scholarly articles and patents have had so little time to attract citations and the resulting drop off is so steep that these additional points create essentially only noise. Moreover, there is a chance that patent applications filed in 2012 have not yet been recorded as of the writing of this paper. This leaves 23 and 16 years of observations for scholarly articles and patents, respectively.

2.2 Summary Statistics

First, we summarize the data by institution. There are forty in total. Texas A&M - Main Campus spends the highest amount on non-social non-medical science research, at $132 million, followed by the University of Georgia. The mean level is $49 million. Texas A&M - Main Campus also spends the most in total non-social science and engineering, at $259 million, followed closely by the University of Wisconsin - Madison. The mean level is $98 million.

The University of Wisconsin-Madison publishes the highest number of scholarly articles, at an average of over 1,800, followed by the Stanford University and the University of Michigan, Ann Arbor. The average number is 820. Stanford University also has the highest average number of related citations, at an average of over 61,000, followed by the University of Wisconsin-Madison and the University of Washington (main campus). The average number is 22,336. Stanford University tops the list of new patent application filings and the citations that accrue to them, at 156 and 3,429, respectively. The University of Texas at Austin is second, with 117 and 2,205, respectively. The mean levels are 34 and 570, respectively.

Next, we summarize the data by year. The average level of non-social non-medical science expenditures grows from $24 to $75 million from 1987 to 2011, while the average level of total non-social science and engineering expenditures grows from $41 to $165 million over the same period. This is an average compound growth rate of 5% for the former funding measure and 6% for the latter. The funding measures are monotone increasing over the panel, with a few exceptions. In 1994, 2004, and 2010, both funding measures drop relative to the year before (in nominal terms). These years directly follow the peak unemployment periods of the last three US recessions.[23] Over the same period, scholarly articles grow at 3.2% while patent applications grow more than twice as fast, at 7.2%. There is considerable variation across schools within each year, but both variables tend to increase monotonically over the panel. The time series of citations is more complicated, since the amount of time other work has to cite these articles and applications is falling over the panel. Both citations are monotonically increasing up to and including 1998

[23] Peak unemployment hit 7.8% in 1992, 6.3% in 2003, and 10.0% in 2009 for the 1990s recession, 2000s recession, and "Great Recession," respectively. Source: "Business Cycle Expansions and Contractions." NBER Website. March 5, 2015.

and then monotonically decreasing after and including 2005. In any case, all main empirical specifications below include year fixed effects, so these issues should not present a problem.

3 Empirical Model

3.1 Overview

We aim to better inform policymakers and administrators about the impact to scientific output from an additional dollar of investment in university research. Estimating this requires addressing two empirical issues. The first comes from the fact that high quality institutions attract big grants as well as big ideas. This causes parameter estimates to be upward biased and suggests that, at a minimum, removing the institution-specific means and time trends from the data is required. However, this still leaves open the question of endogeneity and, as Adams and Griliches [1998] note, probably exacerbates the second issue, an errors-in-variables problem. When the data include long-term projects with multi-year payoffs, tying research outcomes to the expenditures that generated them becomes difficult. Even if a tight causal relationship exists, estimating it can be impossible without information that the econometrician rarely has access to. In the case of the multi-billion dollar Large Hadron Collider at CERN, construction began ten years prior to the first experiments. In the case of the Stanford Linear Accelerator Center, researchers still benefit from portions of the initial $114 million investment in 1961.

The solution is to find a quantity in the data generating process that shifts only marginal research funds and yet is not correlated with the time-varying quality of the institution. To achieve this, we use unexpected NCAA football outcomes. Unexpected wins, for example, shift out research funds and, in turn, drive scientific discovery. Football presumably has a negligible effect on the ability of a school to conduct cutting edge research, and so is excluded from the outcome variables except through funding—especially one or two years into the future.

Timing

Our assumptions regarding the temporal relationship between the variables are as follows: football outcomes impact the level of research in the subsequent period and scholarly articles in the period subsequent to that. Since patent applications usually need to be filed with the USPTO prior to discussing findings in a public forum, i.e. seminar or conference, the patent filings are typically concurrent with the research. Figure 5 illustrates these relationships using our first year of data.

[Figure 5 about here.]

The first period is fiscal year 1988. This period covers regular season football, which is played in the fall of 1987, as well as post-season football, which is played in January of 1988. Football outcomes impact incoming unrestricted funds during this period, including playoff "bowl" proceeds, alumni donations, and the pre-sale of the next season's seats and broadcasting rights. Changes in these incoming funds are budgeted out and spent in the following period, fiscal year 1989. Research is conducted. Alongside or immediately following the research, scientists file patent applications, which must legally precede any dissemination of the findings. The final period is calendar year 1990. Successful research carried out in the second period will be published in journals during this period. The temporal relationship between football, expenditures, and publishing is an assumption we discuss in detail in a later section.

3.2 Specification

The first stage assesses the relationship between the instrument and the endogenous regressor. Specifically, we estimate the following:

$$LogNonFedExpenditures_{i,t} = \alpha_0 + \alpha_1 Football_{i,t-1} + \mu_i + \delta_t + \gamma_i t + \nu_{i,t} \tag{1}$$

where i denotes institution, t denotes the fiscal year, $LogNonFedExpenditures$ denotes the log of non-federal research expenditures, $Football$ denotes the difference between postseason and preseason Associated Press votes (standardized across polls), μ and δ denote school and time dummies, and γ captures the school-specific time trend (omitting the superscripts). We use first stage estimates, $(\hat{\alpha}_0, \hat{\alpha}_1, \hat{\mu}_i, \hat{\delta}_t, \hat{\gamma}_i)$, to generate predicted values for $LogNonFedExpenditures_{i,t}$, denoted $LogNon\widehat{FedExp}enditures_{i,t}$.

To estimate the dollar elasticity of scientific output, we regress the log of each of our four output measures on the predicted values from the first stage. The four estimating equations are given by the following:

$$LogArticles_{i,t} = \beta_0^1 + \beta_1^1 LogNon\widehat{FedExp}enditures_{i,t-1} + \kappa_i^1 + \phi_t^1 + \lambda_i^1 t + \epsilon_{i,t}^1 \tag{2}$$

$$LogArticleCites_{i,t} = \beta_0^2 + \beta_1^2 LogNon\widehat{FedExp}enditures_{i,t-1} + \kappa_i^2 + \phi_t^2 + \lambda_i^2 t + \epsilon_{i,t}^2 \tag{3}$$

$$LogPatents_{i,t} = \beta_0^3 + \beta_1^3 LogNon\widehat{FedExp}enditures_{i,t} + \kappa_i^3 + \phi_t^3 + \lambda_i^3 t + \epsilon_{i,t}^3 \tag{4}$$

$$LogPatentCites_{i,t} = \beta_0^4 + \beta_1^4 LogNon\widehat{FedExp}enditures_{i,t} + \kappa_i^4 + \phi_t^4 + \lambda_i^4 t + \epsilon_{i,t}^4 \tag{5}$$

where κ and ϕ denote school and time controls and λ captures the school-specific time trend (again, omitting superscripts). (2) and (3) use lagged expenditures while (4) and (5) use contemporaneous expenditures. For identification, we require that $Football_{i,t-1}$ is uncorrelated with $\epsilon^1_{i,t+1}$, $\epsilon^2_{i,t+1}$, $\epsilon^3_{i,t}$, and $\epsilon^4_{i,t}$, and that $Football_{i,t-1}$ is a sufficiently strong predictor of $LogNonFedExpenditures_{i,t}$. We cluster our standard errors at the university level, which allows for arbitrary correlation of the unobservables within a university over time, i.e. the squared sum of regressor and error are required to have the same distribution across clusters. In theory, we could also allow for arbitrary correlation of the unobservables within-year in the same specification, as utilized in Petersen [2009], but this is too steep a requirement of the data. As one of our robustness checks, we tested an alternative specification that clustered at the year level and resulted in smaller standard errors, so we did not include these results (although they are available on request). β_1 is the parameter of interest.

We also estimate the dollar cost of a patentable idea (or, to be precise, an idea that the researcher and institution deem worthy of a patent application). To translate the elasticity estimate into level changes, we multiply the reciprocal of this elasticity—roughly the percent change in research expenditures required per one percent change in patent applications—by the average ratio of expenditures to applications. Thus, the cost estimate equals

$$\frac{1}{N}\frac{1}{T}\sum_i\sum_t \hat{\beta}^3_1 \frac{NonFedExpenditures_{i,t}}{Patents_{i,t}}$$

where N is the number of schools.

There are two potential concerns about the exclusion restriction. Both seem small. One occurs if unexpected college football outcomes drive research outcomes, whether in the laboratory or publication process. This includes the case where, for example, football success may attract researchers that are inherently more productive on average. Previous work like Anderson [2012] has shown that the undergraduate student body does improve after teams win. This same argument is unlikely to hold for graduate students and faculty. Another occurs if a third factor simulatenously improves both football and research outcomes, but goes unnoticed by the Associated Press voters. Since the reputation and career prospects of these sports writers and broadcasters depend on the accuracy of their predictions and their perceived access to information, this also seems unimportant. Nonetheless, evidence in the "Exogeneity Check" section provides further support for the instrument.

4 Results

4.1 From Football to Money

Our first stage results assess the relationship between unexpected football outcomes and research expenditures. Table 2 reports these results. Each specification includes university and time fixed effects as well as university-specific time trends. Columns 1-2 show that a one thousand unit change in the vote difference would increase non-medical non-social science expenditures by 3.3% and total non-social science and engineering expenditures by 2.6%. These estimates are significant at 99.6% and 97.5% levels, respectively. Columns 3-4 show that this same change would increase non-medical non-social science expenditures by \$1.775 million and total non-social science and engineering research expenditures by \$1.966 million. The first of these estimates is significant at the 99.3% level, but the second is not precisely estimated. The fit of these specifications range between 95% and 98%, which is not surprising given the large number controls.[24]

[Table 2 about here.]

These estimates square with stylized facts about college football and finances. A one thousand vote change is approximately equal to, for example, a move from 17th place to 1st place or from an unranked position to 10th place. The comparison is imperfect, but this translates to a \$60 million revenue change in Table 1. Our discussions with administrators suggest that roughly five to ten percent of cash flow changes find their way back to university research, and translate into somewhere between \$3 million and \$6 million of additional funding. Since funds are shared between social and non-science departments, and since higher revenues translate to higher costs—for example, hiring more security guards at games to monitor larger crowds at games—then our estimates are in line with what one would expect.

4.2 From Money to Scholarly Articles

To assess the impact of money on science, we begin with the relationship between research expenditures and academic publishing behavior. Table 3 reports these results. This table, as well as the three that follow, present the OLS estimates in the first five columns and the 2SLS estimates in the latter five. Our main findings are in the final column. We find that the dollar elasticity of scholarly articles is 0.310, after controlling for school and time fixed effects as well as school-specific time trends. The instrument, lagged unexpected college football success, provides exogenous variation to science and engineering research

[24] Raw vote differences are used here so the coefficients can be easily interpreted. In the 2SLS results below, vote differences are normalized across years to improve comparability and improve power.

expenditures sourced from the university. The estimate is significant at 99.2%. The F-statistic of the accompanying first stage is 10.98.

[Table 3 about here.]

The sharp contrast with the OLS results is striking. Our main elasticity estimate is nearly ten times what results from an OLS specification with the same level of controls, which would lead policymakers to underestimate the returns to funding scientific research and presumably under-invest in it. One potential issue is that the instrument is identifying a local average treatment affect that is substantively higher than the average elasticity of the sample schools (or sample school-years). This would happen if the sensitivity of the schools' budgets to football outcomes are correlated with the schools' elasticity. If anything, we would expect this to go in the opposite direction—with schools transforming dollars to discoveries at the highest rates also being the schools whose budgets are least affected by football.

More likely the issue is a rather serious errors-in-variables problem for the OLS. The difficulty in temporally tying budgets to discoveries is at the heart of the problem. For example, portions of the $114 million investment in the Stanford Linear Accelerator, built in 1961, generated research for years afterwards. In projects like this, operating expenses may precede experiments for many years, weakening the link between research budgets and articles in the subsequent year and attenuating the elasticity estimates.

To explore this point further, we remove institution specific controls. In fact, removing the institution-specific time trend alone results in a nearly tenfold increase in the estimated elasticity (without much relative change in precision). It is, unfortunately, impossible to say whether the sharp rise is attributable to the mitigation of the errors-in-variables problem or to the re-introduction of institution specific unobservables that drive both expenditures and scientific output. Removing the institution or year fixed effects does not further change the estimates much. It seems that whatever the relative contribution of the errors-in-variables problem or the omitted variable bias may be, their combined effect varies in a complicated way—over time and within the institution.

Our pooled OLS estimates are at the bottom end of those found by Adams and Griliches [1998]. In the presence of only time fixed effects and three high-level institutional controls (for top ten public university, top ten private university, and other private university), they find a dollar elasticity of scholarly articles of between 0.4 and 0.7. The school fixed effects also have the same impact on their OLS results that they have on ours: they find an elasticity of roughly zero.

An important caveat follows for policymakers that wish to use this figure to predict returns to an aggregate national increase in research funding. Since the predicted variation in expenditures is linear in the instrument, unexpected losses hurt research budgets as much as unexpected wins help them.

Thus, our instrument transfers money between schools rather than shifting aggregate annual spending up or down. If these transfers are merely luring scarce assets between institutions, and if these scarce assets—like high-output scientists—are inelastically supplied in the short-run, then our estimates are uninformative about how scientific output responds to aggregate funding increases.[25] This is unlikely. Small and temporary shifts in funding do not drive expensive and long-term commitments like faculty hiring. Faculty also, by casual observations, are not perfectly mobile. Finally, successful scientists tend to attract federal grants so their movement would shift federal research budgets, but our exogeneity check below reveals this is not the case. Instead, conversations with administrators and reseachers suggested an increase in materials purchases and technical staff hires. They also suggested the latter tend not to have or be in pursuit of an advanced degree, since adding doctoral students and post-doctoral fellows are typically—like faculty—long-term and costly commitments. Exploring precisely how universities or the scientists within allocate these funds is beyond the scope of this paper but an important question we leave to future research.

4.3 From Money to Scholarly Article Citations

Next, we consider the citations that accrue to the aforementioned articles. Table 4 reports these results. We find that the dollar elasticity of article citations is 0.590. The result is significant at 97.2%.

[Table 4 about here.]

The larger coefficient on citation-weighted articles squares with intuition. Scholars make extensive-margin decisions about whether to take on more projects. They also make intensive-margin decisions about how much to invest in those they already plan to take on. The article count can be thought of as this extensive margin while the citation-weighted count captures both. To see this, considering the limiting case where researchers facing windfall funding invest only in improving projects they already plan to take on: the number of articles would show no change while the citation-weighted count would fully-reflect the investment. The fact that the citation weighted estimate is close to twice the no-weight estimate suggests scholars are splitting the investment across these margins.

This is, of course, only one possible interpretation, and Adams and Griliches [1998] propose two interesting alternative views. The first is that as Ph.D. students become junior faculty at smaller schools, papers derived from their doctoral work will be incorrectly attributed to the school that hired them. However, this problem will be partially corrected if these papers happen to cite scholars at their degree-

[25] An aggregate increase aimed at universities may draw scientists away from the private sector, although crowding out hardly seems like a policy goal. It may also draw scientists from abroad, but again this hardly seems like a first order policy goal.

granting institution. The second is that larger programs tend towards basic research, which is more likely to have "hit" papers. We prefer our interpretation of the relative magnitudes since the ratio of articles to citations is robust to the inclusion of institution fixed effects and institution-specific time trends.

The errors-in-variables problem discussed in the preceding section again seems an issue for OLS specifications. Although the pooled OLS specification yields a relatively precise estimate of 0.374, the addition of the full set of controls yields an imprecise estimate of 0.057. These results are, again, near the bottom end of the Adams and Griliches [1998] range. They find a dollar elasticity of article citations of between 0.6 and 0.9 without school fixed effects but close to zero effect with school fixed effects.

4.4 From Money to Patents

To assess the impact of money on translational and applied science output, we assess the relationship between research expenditures and patenting behavior. Table 5 reports these results. We expand our funding data to encompass total non-social science and engineering disciplines, rather than non-medical non-social science only.[26] We find that the dollar elasticity of patent applications is 1.91. This result is significant at 96.2% and the corresponding first stage F-statistic is 11.18. This elasticity is surprisingly high and implies increasing returns to research spending, i.e. for each proportional increase in research expenditures, new patent applications will rise by more than 1%. The contrast with the OLS coefficients are even more striking than in the case of scholarly publications. Here, the elasticity from the main specification is between two and three times the precisely-estimated OLS coefficient. Moreover, it is nearly one hundred times the imprecisely estimated OLS estimate with a full set of controls and more than twice the upper bound of the 95% percent confidence interval around that estimate.

[Table 5 about here.]

We also estimate the dollar cost of generating a patentable idea. This entails dividing the ratio of non-federal research spending to patents by the elasticity estimated above, and averaging across schools and, where applicable, time. Using only the most recent years' spending-to-patent ratios yields a cost of $2.612 million. Using all years' ratios yields a cost of $2.975 million. University patenting has increased steadily since the Bayh-Dole Act of 1980, which allowed universities to retain ownership over their publically-funded intellectual property. Thus, the first figure should better predict the response to a current policy change. Despite broader coverage in terms of disciplines and a longer panel, these figures are quite close to—although slightly lower than—the roughly $3.3 million cost estimated in Azoulay et al. [2014].

[26] The University of Oregon was the only school in our sample without an identifiable Assignee/Applicant name or DWPI Assignee code in Thomson Innovation. Since the University of Oregon is also the only school in our sample without the School of Engineering, we drop it from the patent analysis portion of the paper.

4.5 From Money to Patent Citations

Finally, we assess the relationship between research expenditures and patent citations. Table 6 reports these results. Our main specification yields an elasticity of 3.30, and this result is significant at 98.8%. This estimate is nearly twice the elasticity on the count of patent applications, again suggesting researchers are roughly splitting their time between launching new projects and improving the quality of existing projects. Although the outcome data comes from an entirely separate source than the scholarly article data, it is reassuring to see the ratio of documents to their accrued citations be the same for both scholarly articles and patent applications.

[Table 6 about here.]

Nonetheless, this suggests strongly increasing returns to research investment at the margin and may be surprising. However, when one considers the large amount of fixed investment, both in terms of faculty and facilities, then if the bottleneck for research—as recent press has indicated—is at the funding level, these elasticities both seem reasonable. Of course, while one would need to estimate the real returns from academic patents to figure out whether the government and universities are funding the right level of research, our results appear to support arguments for an increase in research spending.

4.6 Exogeneity Check

College football should impact only research funds provided by non-federal sources and have no effect on funds provided by the federal government. We observe the dollars contributed from these sources independently in the data and use this to strengthen the exogeneity argument for our instrument. That is, if some unobservable factor that varied by institution and time was driving unexpected football success, scientific discovery, and non-federal research funding, then it is likely to show up in federal research funding as well. Figure 6 addresses this potential confound. The y-axis shows research expenditures, by source, while the x-axis shows the instrument. School and year effects, as well as a schools-specific time trend, have been removed from both.

[Figure 6 about here.]

The left panel reports the strong, positive relationship between the instrument and research expenditures sourced from non-federal entities. This is merely the graphical representation of the first-stage results. The right panel, in contrast, reports the lack of any relationship between the instrument and federally-sourced research expenditures.

In fact, we can statistically separate the effect on these two sources. To do so, we pool together federal and non-federal data, so that an observation is university-year-source specific. We interact the full set of controls with a dummy variable for non-federal expenditures so that our university and year fixed effects as well as our university-specific time trends are source specific. The standard errors are clustered at the university-source level. Table 7 reports the results of this exercise. In the first column, the left-hand side variable is the log of non-medical non-social science expenditures. The instrument has a precisely estimated zero effect on the federally-sourced portion of expenditures. That is, the coefficient is not significant and the 95% confidence interval spans a relatively narrow range of -0.75% to 0.78%. In contrast, the coefficient on the interaction term—representing the impact of the instrument on the non-federally-sourced portion of expenditures—is positive and significant at over 99%. The second column shows analogous results when the log of total non-social science and engineering expenditures is used as the left-hand side variable.[27]

[Table 7 about here.]

We interpret this as support for the instrument. As discussed in the "Empirical Model" section, there are two potential issues with identification. The first occurs when unexpected football success causes success in the research or publication process. The second occurs when a third unobserved factor simulatenously drives football and research outcomes. For example, a charasmatic new college president could enhance both football and faculty recruiting. [28] Both issues seems *prima facie* unproblematic, but Figure 6 lends additional proof. If the instrument causes, or is the result of, an aggregate productivity shock at the university-year level, then scientists could attract more grant money, which the data rejects. Moreover, if the instrument enables the university to recruit more productive faculty, or is the result of a factor that enables the same, then these star faculty should bring with them large federal grants. This, too, is rejected by the data.

4.7 Discussion of Timing

The empirical specification considers a particular temporal relationship between football, funding, and publishing. Misspecification of this relationship can result in biased estimates relative to the policy-relevant parameters. Below we show that although the impact of football extends to periods other than what the model strictly specifies, the impact of funding does not. This leaves the estimates unbiased. Last, we discuss factors that drive the timing of the expenditures-publications relationship, which may strike social scientists as compressed.

[27] We thank James Lee for suggesting this specification.

[28] Our restriction to unanticipated football outcomes would further require that the star football recruits either go unnoticed by poll respondents in the pre-season poll, or join after the pre-season poll is completed.

We first assess misspecification in the first stage. Our analysis assumes that football in period t mainly impacts funding in period $t+1$. However, football can impact funding at t if, for example, football inspires some immediate and directed donations to academic endeavors. It may also impact funding at $t+2$ and later if team success at the end of the season influences the starting point of success for future seasons. It should not, of course, impact funding at $t-1$, a period prior to the football season. Table 8 reports the relationship between funding and the seven prior years' instrument values as well as the current year and following year instrument values. A full set of controls are included. The first column reports the impact on the log of non-medical non-social science expenditures while the second reports the impact of the log of total non-social science and engineering expenditures. These results confirm our intuition about the first stage timing. In both cases, funding is most strongly impacted by one-year lagged instrument values and is not meaningfully impacted by the future value of the instrument. There is a non-trival impact from the instrument in the contemporaneous period and the instrument lagged more than one year. However, the coefficients tend to drop monotonically in terms of both magnitude and significance.

[Table 8 about here.]

Expenditures, on the other hand, largely impact output in a single year, so the estimates are unbiased despite the impact of football being spread out. Table 9 reports this result for academic publishing. The left-hand side variable is the log of scholarly articles. The right-hand side variables are predicted values of leading, contemporaneous, and one- to three-year lagged research expenditures. In line with the model, the largest and only significant coefficient is on once-lagged expenditures. Table 10 reports the result for the case where the publishing measure is new patent applications. In line with the model once again, the largest and only significant coefficient is on contemporaenous year expenditures.

[Table 9 about here.]

[Table 10 about here.]

That funding impacts subsequent-period scholarly articles may strike readers as too fast, but several factors explain this. Recall that research budgets are reported on a fiscal year basis while output is recorded on a calendar year basis, so there is an added six month gap between funding and publishing periods. Many projects are bottled-necked due to funding. In these cases, budgets will be spent soon after they are replenished, so the actual lag we measure may be close to two years rather than one. Futhermore, non-social non-medical science is, at least anecdotally, faster to conduct than social science research. NSF grant data provides evidence of this. For example, among all grants given out in 2000, 2005, and 2010, 26% resulted in the original grant year for physics-related proposals while only 5.4% of economics-related proposals did. Among grants over the same time period that resulted in at least one publication, 46% resulted in journal publications in the original grant year for physics-related proposals while only 13% of economics-related proposals did. The publication process is correspondingly fast. The receipt-to-acceptance time for manuscripts published in non-social non-medical science journals is around a third of those published in economics journals. For example, the average time between first submission and final publication was between 13 and 22 weeks at the five main journals of the American Physics Society (Pattard [2010]) but 62 weeks at the *American Economic Review* (Moffitt [2009]).[29] Also, natural science disciplines in particular tend to rely more on short papers, proceedings, and letters, which have much shorter review times. For example, "rapid communication" section of the five main journals of the American Physics Society has an average receipt-to-acceptance time of between 9 and 15 weeks and a minimum of only two days.

The timing of patent filings is driven by different factors. To ensure intellectual property protection of an idea, scholars must submit their new patent application to the USPTO ahead of giving seminars or conference talks. On top of that, patents are faster to write and assigned a "publication date" before the review process. Taken together, it is not surpring that the data indicates scientists file in the same period that research budgets are replenished. With respect to the timing of patent filings, our results are in line with earlier work in different settings. For example, Hall et al. [1986] studied manufacturing industry investments to R&D from 1972 to 1979 and stated, "R and D and patents appear to be dominated by a contemporaneous relationship."

5 Conclusion

Unanticipated within-season football success impacts school-sponsored research, providing rich exogenous variation that identifies the impact of money on science. An instrumental variable approach is important to study this relationship for two reasons. First, large grants are typically awarded to institutions that would otherwise attract big ideas, so an approach that ignores this endogeneity will recover upwardly biased parameters. Second, funding data include long-term projects with payoffs to researchers over many years, making it difficult to tie shifts in spending to shifts in scientific outcomes and creating an errors-in-variables problem that attenuates estimates toward zero. Our approach yields a dollar elasticity of scholarly articles at 0.31 and of article citations at 0.59. It also yields a dollar elasticity of new patent applications at 1.91 and of patent citations at 3.30. If citations are rough measure of quality, then these results suggest researchers are splitting their time between launching new projects and improving the quality of existing projects. We find it costs universities, at the margin, approximately $2.6 million to generate an idea worthy of filing a

[29]This comparison is drawn from 2008.

patent application.

The inclusion of school specific controls, i.e. fixed effects and a school specific time trend, improved the first stage power but ultimately did not change the elasticity much for the 2SLS specifications. Their inclusion sharply reduced OLS estimates, which tended toward zero for all outcome measures. This highlights the importance of using instruments to "pick out" marginal expenditure shifts that can be tied to scientific outcomes. Without them, this exercise would understate the returns to university R&D and lead policymakers to under-invest, which highlights the need to an instrumental variable that provides rich short-term variations in funds.

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Appendix

Allocating patent filings to universities

Identifying cohesive patent portfolios and patent applicants and assignees can be a difficult task. Numerous variations in names of patent-seeking institutions appear in USPTO records caused by either the variation in patent-prosecuting law firms or human errors and incorrectly spelled names. For example, there are 157 variations of assignee/applicant names grouped under the "University of California" umbrella in our Thomson Innovation patent sample. These names range from "*The Regents of the University of California*", "*University of California Berkeley*", "*University of California Los Angeles*", "*The Regents of the University of Caliofornia*", to the "*The Regents of the University of California*". In addition, to better identify university owned patents and patent applications, we utilize DWPI assignee classification available in Thomson Innovation: a unique 4-letter identifying code assigned to approximately 22,300 international patentees. For example, The University of California is assigned a unique 4-letter code "REGC", and in order to retrieve all patent records assigned to the University of California, we query Thomson database for all variations of assignee/applicant string grouped under "University of California" and associated with "REGC" assignee code for earliest patent priority years 1996-2011. It is important to note that, while we collect patent data starting with 1987, our panel officially starts in 1996. We start the panel in 1996 because of the effects that the international harmonization of the Unites States patent system in early 1990's had on university patenting behavior. As shown in Appendix Figure I, one of the patent law amendments with a significant impact was the introduction of provisional patent applications in June 1995.[30]

[Figure 7 about here.]

Since the introduction of provisional patenting provided a convenient solution for academic researchers faced with publish-or-patent-first dilemma, it resulted in a sharp increase in university patent applications. A published article, a conference presentation, or even as much as a conversation describing an invention before a patent is filed represents a public disclosure, and can deem that invention unpatentable. To the extent that the scientific work in academia is first and foremost driven by article considerations in peer-reviewed journals, provisional patent applications are an exceptionally good fit for this environment as they enable the university to lock an early priority date, while providing additional 12 months for inventors to publish, disseminate and improve the invention. Universities use provisional patent applications to

[30] As described in 35 U.S.C. §111, a provisional patent application allows an applicant to file an application with specification only, and without any formal patent claims, oath, declaration, or any prior art disclosures. A provisional patent application establishes an early patent filing date, but does not evolve into an granted patent unless the applicant converts it into a full patent application within twelve months. It effectively allows an applicant to lock-in a patent priority date, without being subjected to the cost of a regular patent application filing.

reduce uncertainty surrounding market value of inventions and make a more informed decision of whether to prosecute full patents. Indeed, many university Technology Transfer Offices laud provisional patent applications as the first order of business after being informed of a new invention.[31]

Prevalence of provisional patenting in academia was the main reason behind our decision to stop our panel with patent applications filed in 2011. Since provisional patent applications take 12 months before they are published, patent application data from 2012 would be missing all provisional patents applied for in that year, and would result in a truncated patent count.

We use priority dates rather than application dates to count patent records because priority years most closely correspond with the date when the invention was *first applied for*. While the patent priority date is most often no different than the regular patent application date, in a case of a converted provisional application, a priority date will be earlier than the regular application date. This is especially the case when a divisional or a continuation application was filed. In addition, we use the DWPI Patent Family list available in Thomson Innovation database to assign all retrieved patent records to unique groups sharing the same priority application. This enables us to more closely identify patent groups surrounding the same invention and ensures that we do not overcount patent records in the sample. Each DWPI Patent Family is counted only once, and all forward patent citation counts are aggregated on a DWPI Patent Family level.

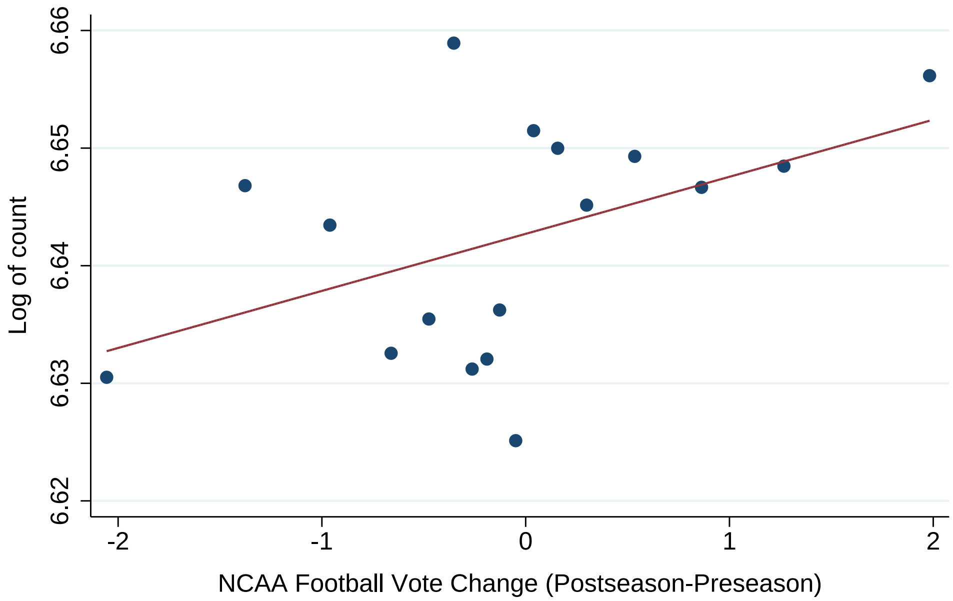
To further exacerbate the problem of allocating patent applications to universities, some university systems do not specify campus locations where the invention was made when filing their patents. For example, almost 75% of all patent applications from University of California System in our sample are assigned to "The Regents of The University of California" without any additional information about invention-originating campus. Consequently, we do not know if the invention was made at The University of California at Berkeley, The University of California at Los Angeles, or any other campus in the system. Since our instrument works on the individual campus level only, and does not propagate through the whole system, we need to allocate patent applications to individual campuses within the university. In other words, unexpected success of The University of California at Berkeley football team will not impact R&D expenditures at The University of California at Los Angeles, and vice versa. To rectify this problem, we use the inventor's home address information provided on US patent records and use Google Maps API to calculate the "by car" estimated travel time from inventor's home address to every campus in the university system. We then systematically examine the patent portfolio and count a patent as originating at

[31] For example, see Office of Vice President for Research at Penn State http://www.research.psu.edu/patents/protect-your-invention/what-happens-after-submission), Innovation and New Ventures Office at Northwestern University (http://www.invo.northwestern.edu/process/assessment-patents), Northeastern University Center for Research Innovation (http://www.northeastern.edu/research/cri/inventors/commercialization-process/),or Boston University Technology Development (http://www.bu.edu/otd/for-researchers/technology-transfer-process/patentapp/).

a specific university campus if at least one inventor lives less than 26 minute drive from that campus.[32]

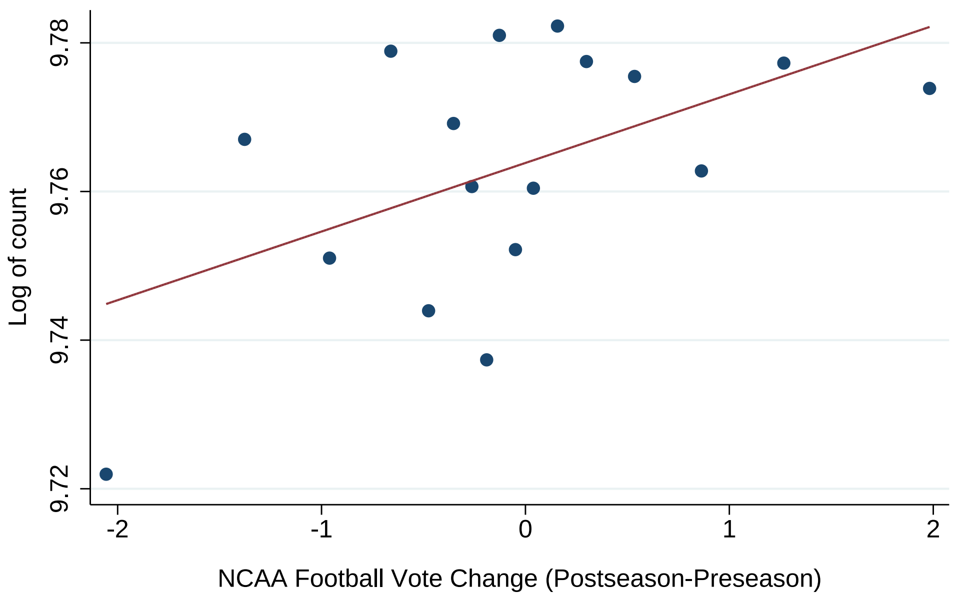
[32]This distance is based on the 2013 US Census American Community Survey estimate of mean travel time to work in the United States of 25.8 minutes. Our results are robust to different travel times: travel times of 15, 20 and 30 minutes did not cause any significant changes in our outcomes.

Figures



Source: *Thomson Reuters* for publication data and *Associated Press* for football data.

Figure 1: *Football and scholarly articles*



Source: *Thomson Reuters* for publication citation data and *Associated Press* for football data.

Figure 2: *Football and scholarly article citations*

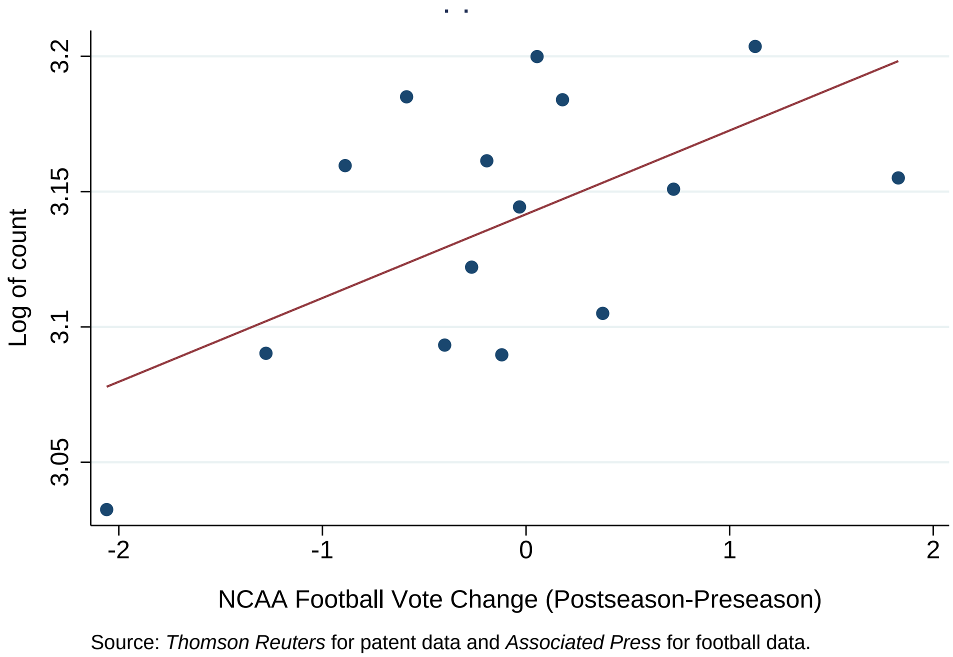


Figure 3: *Football and new patent applications*

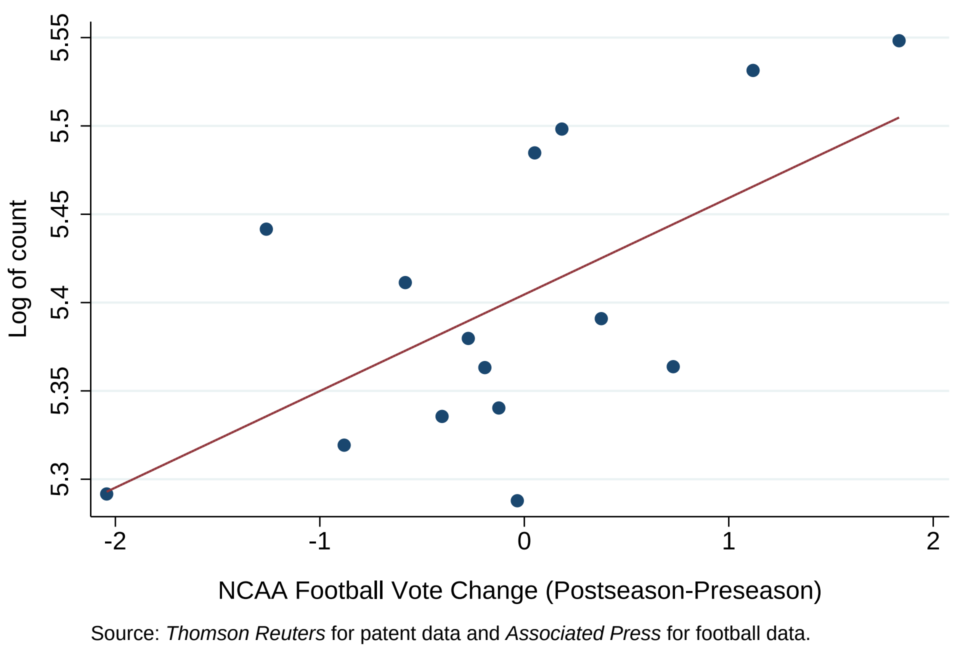


Figure 4: *Football and patent citations*

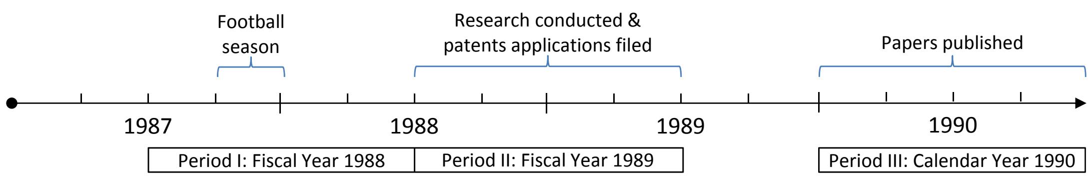


Figure 5: *Timing of football, research, and publishing*

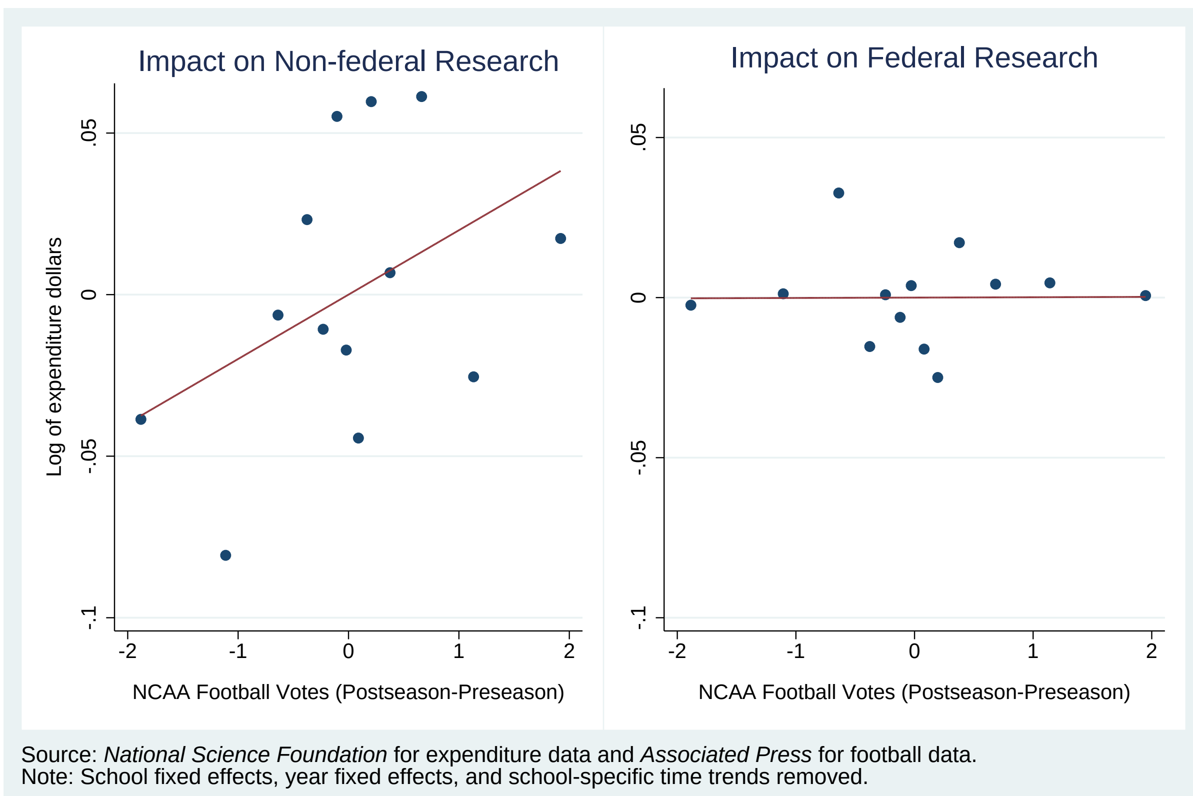


Figure 6: *Impact of football on federal vs. non-federal funding*

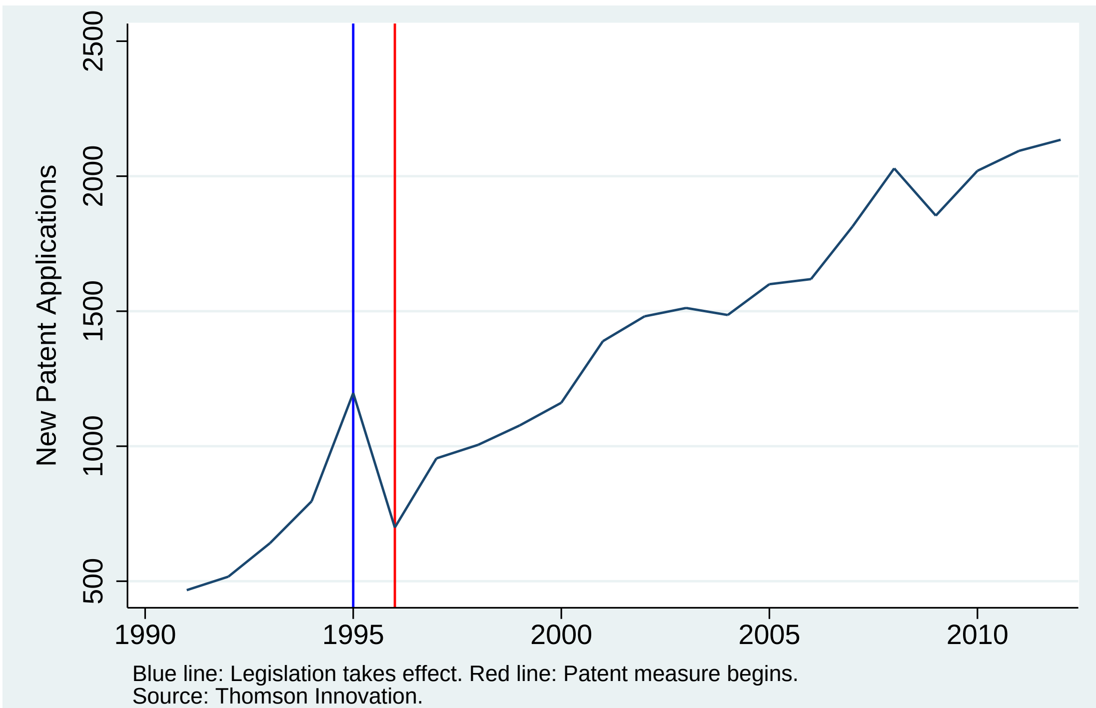


Figure 7: *Patent applications filed over time*

Tables

Table 1: *Football and university finances*

	Football			# Seasons	
		As a percent of all			
	Revenue	Athletics Revenue	Tuition Receipts	Ranked 1 or 2	Unranked
(NCAA Football: 12 game season)					
The Univ of Texas at Austin	$109,400,688	66%	23%	2	9
The Univ of Alabama	88,660,439	62%	25%	2	9
Univ of Michigan-Ann Arbor	81,475,191	66%	9%	1	5
Univ of Notre Dame	78,349,132	72%	29%	3	10
Univ of Georgia	77,594,300	79%	23%	1	9
Auburn Univ	75,092,576	73%	26%	2	8
Univ of Florida	74,820,287	58%	23%	4	2
Louisiana State Univ A&M College	74,275,838	63%	32%	2	10
Univ of Oklahoma Norman Campus	69,647,986	56%	31%	1	9
Univ of Arkansas	61,492,925	62%	8%	0	12
Ohio State Univ-Main Campus	61,131,726	49%	4%	4	4
Pennsylvania State Univ-Main Campus	58,722,182	56%	9%	1	8
Univ of Washington-Seattle Campus	56,379,534	66%	32%	1	13
Univ of Nebraska-Lincoln	55,866,615	64%	16%	3	5
Univ of Iowa	55,648,679	52%	20%	0	12
The Univ of Tennessee	55,359,423	50%	17%	1	8
Univ of Oregon	53,982,076	66%	13%	1	12
Texas A & M Univ-College Station	53,800,924	69%	27%	0	10
Univ of Wisconsin-Madison	50,641,993	35%	8%	0	12
Michigan State Univ	47,869,615	60%	5%	0	16
(For comparison)					
Median Pro Football Team (16 game season)	$269,000,000				
Median Pro Baseball Team (162 game season)	214,000,000				
Median Pro Basketball Team (82 game season)	139,000,000				
Median Pro Hockey Team (82 game season)	80,500,000				

Source: NCAA.org (college athletic revenue), US Dept of Education National Center for Education Statistics (tuition), Associated Press (team rankings), and Forbes.com (professional sports revenue).

Table 2: *The impact of football on non-federal research expenditures*

	(1)	(2)	(3)	(4)
1000 Vote Change	0.0327***	1,775***	0.0256**	1,966
	(0.0108)	(618.3)	(0.0110)	(1,226)
Constant	115.9***	1.053e+07***	124.2***	2.983e+07***
	(0.185)	(10,376)	(0.190)	(19,981)
School FE	x	x	x	x
Year FE	x	x	x	x
School Time Trend	x	x	x	x
R-squared	0.965	0.956	0.976	0.963
Observations	949	949	949	949
Number of Clusters	40	40	40	40

*Note. - Standard errors, clustered at university level, in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.*

Table 3: *The impact of money on scholarly articles*

	OLS Specifications					IV Specifications				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lagged Log Expenditures	0.456***	0.438***	0.438***	0.0658**	0.0349**	0.596	0.603	0.442	0.471	0.310***
	(0.0962)	(0.105)	(0.0419)	(0.0280)	(0.0171)	(0.486)	(0.502)	(0.481)	(0.326)	(0.117)
Constant	1.930*	2.220*	0.719**	3.559***	1.313***	0.485	0.449	1.158	0.981	1.233
	(1.038)	(1.168)	(0.289)	(0.208)	(0.189)	(5.046)	(5.437)	(4.690)	(3.326)	(1.210)
School FE			x	x	x			x	x	x
Year FE		x		x	x		x		x	x
School Time Trend					x					x
Observations	869	869	869	869	869	869	869	869	869	869
R-squared	0.422	0.433	0.956	0.983	0.994	0.382	0.382	0.956	0.966	0.989
Number of Clusters	40	40	40	40	40	40	40	40	40	40
F-Stat: 1st Stage						10.98	10.98	10.98	10.98	10.98

*Note. - Standard errors, clustered at university level, in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.*

Table 4: *The impact of money on scholarly articles' citations*

	OLS Specifications					IV Specifications				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lagged Log Expenditures	0.374***	0.435***	-0.243***	0.0743	0.0574	0.651	0.798	1.059	0.426	0.590**
	(0.135)	(0.137)	(0.0697)	(0.0535)	(0.0370)	(0.659)	(0.716)	(1.331)	(0.502)	(0.268)
Constant	5.897***	4.080**	7.900***	4.700***	18.05***	3.037	0.166	-2.084	2.914	16.07***
	(1.450)	(1.518)	(0.480)	(0.395)	(0.654)	(6.813)	(7.739)	(12.97)	(5.120)	(2.736)
School FE			x	x	x			x	x	x
Year FE		x		x	x		x		x	x
School Time Trend					x					x
Observations	869	869	869	869	869	869	869	869	869	869
R-squared	0.179	0.349	0.850	0.962	0.985	0.081	0.191	0.594	0.954	0.974
Number of Clusters	40	40	40	40	40	40	40	40	40	40
F-Stat: 1st Stage						10.98	10.98	10.98	10.98	10.98

*Note. - Standard errors, clustered at university level, in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.*

Table 5: *The impact of money on patent applications*

	OLS Specifications					IV Specifications				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lagged Log Expenditures	0.690***	0.657***	1.017***	0.536***	0.0207	-0.0790	0.0460	2.014**	1.916**	1.914**
	(0.114)	(0.112)	(0.103)	(0.193)	(0.313)	(0.960)	(0.762)	(0.901)	(0.791)	(0.922)
Constant	-4.713***	-4.780***	-6.886***	-3.759**	-2.775	4.037	3.003	-20.08**	-19.29**	-19.23*
	(1.321)	(1.266)	(0.791)	(1.396)	(1.920)	(10.89)	(8.900)	(9.757)	(8.839)	(10.36)
School FE			x	x	x			x	x	x
Year FE		x		x	x		x		x	x
School Time Trend					x					x
Observations	607	607	607	607	607	607	607	607	607	607
R-squared	0.401	0.425	0.836	0.850	0.909		0.125	0.752	0.798	0.851
Number of Clusters	39	39	39	39	39	39	39	39	39	39
F-Stat: 1st Stage						11.18	11.18	11.18	11.18	11.18

*Note. - Standard errors, clustered at university level, in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.*

Table 6: *The impact of money on patents' citations*

	OLS Specifications					IV Specifications				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lagged Log Expenditures	0.609***	0.746***	-0.872***	0.816***	0.129	-0.0488	-0.110	2.251	2.539**	3.302**
	(0.0977)	(0.128)	(0.258)	(0.288)	(0.229)	(1.374)	(1.209)	(1.954)	(1.120)	(1.314)
Constant	-1.527	-2.077	9.529***	-2.006	1.322	5.954	5.366	-20.71	-25.97**	-35.06**
	(1.112)	(1.410)	(1.982)	(1.984)	(1.460)	(15.60)	(14.20)	(21.15)	(12.50)	(14.72)
School FE			x	x	x			x	x	x
Year FE		x		x	x		x		x	x
School Time Trend					x					x
Observations	604	604	604	604	604	604	604	604	604	604
R-squared	0.174	0.395	0.695	0.805	0.857		0.067	0.235	0.760	0.770
Number of Clusters	39	39	39	39	39	39	39	39	39	39
F-Stat: 1st Stage						11.18	11.18	11.18	11.18	11.18

*Note. - Standard errors, clustered at university level, in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.*

Table 7: *Exogeneity check for instrument*

	(1)	(2)
Non-Federal Dummy	35.24***	24.69***
	(0.0738)	(0.0679)
Instrument	0.000113	-0.000298
	(0.00383)	(0.00374)
(Non-Federal Dummy) x Instrument	0.0190***	0.0163**
	(0.00615)	(0.00672)
Constant	-23.12***	-11.64***
	(0.0517)	(0.0528)
School FE	x	x
Year FE	x	x
School Time Trend	x	x
R-squared	0.982	0.984
Observations	1,905	1,905
Number of Clusters	80	80

*Note. - Standard errors, clustered at university level, in parenthesis. *** p<0.01, ** p<0.05, * p<0.1*

Table 8: *First stage timing*

Dep. Var.:	Non-Federal Non-Medical Non-Social Science Expenditures	Non-Federal Non-Social Science and Engineering Expenditures
	(1)	(2)
Instrument: 1 Year Ahead	0.00334	-0.00177
	(0.00729)	(0.00772)
Instrument: Contemporaneous	0.0206*	0.0115
	(0.0105)	(0.00756)
Instrument: 1 Year Prior	0.0316***	0.0242***
	(0.0113)	(0.00853)
Instrument: 2 Year Prior	0.0316**	0.0246**
	(0.0148)	(0.0108)
Instrument: 3 Year Prior	0.0328**	0.0227**
	(0.0128)	(0.0109)
Instrument: 4 Year Prior	0.0221	0.0132
	(0.0139)	(0.0129)
Instrument: 5 Year Prior	0.0213	0.00820
	(0.0129)	(0.0104)
Instrument: 6 Year Prior	0.0162	0.00554
	(0.0128)	(0.00892)
Instrument: 7 Year Prior	0.0116	0.00822
	(0.0144)	(0.0126)
Constant	7.831***	8.146***
	(0.0633)	(0.0626)
School FE	x	x
Year FE	x	x
School Time Trend	x	x
R-squared	0.977	0.984
Observations	673	673
Number of Clusters	40	40

*Note. - Standard errors, clustered at university level, in parenthesis. *** p<0.01, ** p<0.05, * p<0.1*

Table 9: *Second stage timing: scholarly articles*

	(1)	(2)	(3)	(4)	(5)
1 Year Leading Expenditures	0.0204				
	(0.107)				
Contemporaneous Expenditures		-0.00767			
		(0.0976)			
1 Year Lagged Expenditures			0.310***		
			(0.117)		
2 Year Lagged Expenditures				-0.225	
				(0.249)	
3 Year Lagged Expenditures					-0.0297
					(0.176)
School FE	x	x	x	x	x
Year FE	x	x	x	x	x
School Time Trend	x	x	x	x	x
R-squared	0.993	0.993	0.989	0.990	0.994
Observations	949	909	869	829	789
Number of Clusters	40	40	40	40	41

*Note. - Standard errors, clustered at university level, in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.*

Table 10: *Second stage timing: patents*

	(1)	(2)	(3)	(4)	(5)
1 Year Leading Expenditures	1.209				
	(1.999)				
Contemporaneous Expenditures		1.914**			
		(0.922)			
1 Year Lagged Expenditures			0.0623		
			(1.118)		
2 Year Lagged Expenditures				-1.448	
				(1.419)	
3 Year Lagged Expenditures					*-0.558*
					(1.649)
School FE	949	909	869	829	789
Year FE	0.993	0.993	0.989	0.990	0.994
School Time Trend	x	x	x	x	x
R-squared	0.892	0.851	0.911	0.867	0.904
Observations	609	607	607	607	607
Number of Clusters	39	39	39	39	39

*Note. - Standard errors, clustered at university level, in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.*