STRIKING THE BALANCE: UNIVERSITY COMMERCIALIZATION AND SCIENTIFIC RESEARCH PRODUCTIVITY

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ABSTRACT

University-based discoveries that drive economic growth are a natural byproduct of scientific research. However, many of these inventions never realize their full potential value because they "languish" in universities and never diffuse to the broader economy. University technology license agreements are critical tools for idea diffusion. However, some fear that giving scientists more commercial responsibilities will crowd out core scientific tasks like basic research. To assess these competing viewpoints, this Note investigates the impact of university technology licensing on scientists' academic research performance at Stanford University, finding that licensing significantly increases the number of papers that a scientist publishes and providing a promising indication of the complementarity of academic research and technology transfer.

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INTRODUCTION

Scientific advancements born in university labs have long been shown to drive corporate innovation and economic growth.[1] "Pivotal innovations" from across the product spectrum can be traced back to academic origins; from X-rays and mRNA vaccines to e-readers and the World Wide Web, university research has played an integral role in many of the technologies that shape the modern world.[2] Such discoveries are a natural part of academic scientific research. Researchers in fields like biochemistry, for example, are likely to discover potentially patentable (or otherwise protectable) technologies in the course of their academic work.[3] Yet, many university-based discoveries "'languish[]' in the ivory tower, never diffusing out into the economy," and thus fail to "fully realize their potential private and social returns."[4] Today, the university technology license agreement is a critical tool to diffuse these ideas and inventions into the broader economy. These agreements allow a university to license inventions developed in the course of university research either to existing private-sector companies or to start-ups spinning out of university labs.[5]

1. *See*, *e.g.*, Anna Valero & John Van Reenen, *The Economic Impact of Universities: Evidence from Across the Globe*, 68 ECON. ED. REV. 53, 53 (2019) (concluding that "increases in the number of universities are positively associated with future growth"); Naomi Hausman, *University Innovation and Local Economic Growth*, 104 REV. ECON. & STAT. 718, 718 (2021) (identifying "faster growth in employment, wages, and corporate innovation [due] . . . to the spread of innovation from universities"); Lynne Zucker & Michael Darby, *Star Scientists and Institutional Transformation: Patterns of Invention and Innovation in the Formation of the Biotechnology Industry*, 93 PROC. NAT'L ACAD. SCIS. 12709, 12709 (1996) (finding that "[w]here and when star scientists were actively producing publications is a key predictor of where and when commercial firms began to use biotechnology"); Valentí Rull, *The Most Important Application of Science: As Scientists Have to Justify Research Funding with Potential Social Benefits, They May Well Add Education to the List*, 15 SCI. & SOCIETY 919, 919 (2014) (noting that "science is often justified to the public as driving economic growth, which is seen as a return-on-investment for public funding").
2. Jazmin Murphy, *5 Modern-Day Inventions You Didn't Know Were from Universities*, HALO SCI. BLOG (Jan. 30, 2022), https://perma.cc/R4GA-UZTE.
3. *See* Joris J. Heus et al., *Importance of Intellectual Property Generated by Biomedical Research at Universities and Academic Hospitals*, 3 J. CLINICAL & TRANSLATIONAL RSCH. 250 (2017). Also note that university technology transfer offices consider not only patent protection for inventions but also "other forms of intellectual property—copyright, trademark, and/or a trade secret." Randi B. Isaacs, *Inside a University's Technology Transfer Office: Purposes and Goals for Protecting a University's Intellectual Property*, LANDSLIDE, Feb. 2016, at 30.
4. Josh Lerner et al., *The Wandering Scholars: Understanding the Heterogeneity of University Commercialization* (Harvard Bus. Sch. Working Paper No. 24-043), https://perma.cc/BUX2-NRAU.
5. Commercialization is generally seen as an essential tool to ensure that non-academic entities have both the incentive and opportunity to make use of academic discoveries. For example, interviews with several Canadian biomedical researchers suggest "a consensus among most participants that commercialization is the only way to bring innovations in biomedical research to patients." Kelly Holloway & Matthew Herder, *A Responsibility to*

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However, certain policymakers remain hesitant to push for further commercialization of university-based discoveries, citing concerns about the potential downsides of shifting scientists' time and effort away from the lab.[6] For example, some policymakers express concerns that "the commercialization mantra will cause us to abandon . . . open thinking and experimentation without end" and that such "social costs associated with the push to commercialize university research" render university patenting and licensing disadvantageous.[7] They fear that a focus on technology licensing will lead to a decrease in *basic research*—i.e., "study directed toward greater knowledge or understanding of the fundamental aspects of phenomena and of observable facts without specific applications towards processes or products in mind," such as "uncovering the structure of DNA."[8] Faculty also exhibit reluctance to disclose their inventions as part of the technology transfer process, contributing to many institutions' already "slow and limited" growth in technology licensing.[9] Evidence

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Commercialize? Tracing Academic Researchers' Evolving Engagement with the Commercialization of Biomedical Research, 6 J. RESPONSIBLE INNOVATION 263, 263 (2019). Nonetheless, commercialization efforts have had differential success in diffusing scientists' inventions out of universities, with significant heterogeneity across observable characteristics like gender. For example, the Massachusetts Institute of Technology (MIT) Future Founders Initiative arose out of the realization by Sangeeta Bhatia, Susan Hockfield, and Nancy Hopkins that, "[d]espite increasing representation at MIT, female science and engineering faculty found biotech start-ups at a disproportionately low rate compared with their male colleagues." Kate S. Petersen, *MIT Future Founders Initiative Announces Prize Competition to Promote Female Entrepreneurs in Biotech*, MIT NEWS (Nov. 30, 2021), https://perma.cc/T9SJ-CSXV. *See also* Fiona Murray & Scott Stern, *When Ideas Are Not Free: The Impact of Patents on Scientific Research* in INNOVATION POL'Y & THE ECON. 33, 37 (Adam B. Jaffe, Josh Lerner & Scott Stern eds., 2007) (noting that "female academics remain less likely to participate in both scientific research (publishing) and commercial exploitation").

6. Some onlookers also fear that universities may be less capable than the inventor at commercializing a technology. The thrust of these observers' fears is captured in Patricia Campbell's hypothetical wherein the Bell Telephone Company might never have been founded if Boston University owned the rights to Alexander Graham Bell's inventions rather than Bell himself. Patricia E. Campbell, *University Inventions Reconsidered: Debunking the Myth of University Ownership*, 11 WM. & MARY BUS. L. REV. 77, 79-80 (2019).

7. Timothy Caulfield, *Commercialization Creep*, POL'Y OPTIONS (Dec. 1, 2012), https://perma.cc/5S59-4BZZ. Some also express concerns about the impact of commercialization on the future of academic work and, among other things, its independence. For example, in discussing potential university scientist collaborations with British Petroleum (BP), Tadeusz Patzek expressed a "fear[] that professors, following the money, will steer their research toward BP's specified area of commercial interest" rather than researching other energy options that they might have pursued in the absence of such collaboration. Jennifer Washburn, *Science's Worst Enemy: Corporate Funding*, DISCOVER MAG. (Nov. 19, 2007), https://perma.cc/894Z-H6ML.

8. *What Does Basic Research Mean?*, NAT'L INST. OF ALLERGY AND INFECTIOUS DISEASES (Feb. 15, 2023), https://perma.cc/U367-8RBC; U.S. Cong., Joint Econ. Comm., *The Pivotal Role of Government Investment in Basic Research*, 111th Cong., 2d sess., 2010.

9. Paul R. Sanberg et al., *Changing the Academic Culture: Valuing Patents and Commercialization*

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suggests that faculty hesitation relates less to the potential loss of basic research and more to practical matters—e.g., criteria for receiving tenure and academic promotion that have not always taken commercialization activities into account.[10] Thus, the fear that commercial responsibilities will crowd out core scientific tasks like basic research and academic publications sometimes motivates opposition to increased university commercialization.[11]

To assess these competing viewpoints, this Note investigates the impact of university technology licensing on scientists' academic research performance.[12] It uses detailed data on technology disclosures, licenses, and research publications at Stanford University to estimate the net impact of licensing on academic research output. Stanford is a helpful setting for this analysis for various reasons, including that the university, its culture, and its location in Silicon Valley tend to both encourage and attract entrepreneurially inclined researchers.[13] As Richard Zare explained: "'[i]t isn't enough to create new knowledge . . . . You need to transfer that knowledge for the betterment of society.'"[14] The empirical approach described below accounts for both potential benefits, such as sponsored research agreements and industry collaborations, and potential costs, such as additional responsibilities outside of academia that shift scientists' time away from their research in the lab.[15] This Note also builds on the

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Toward Tenure and Career Advancement, 111 PROC. NAT'L ACAD. SCIS. 6542, 6542 (2014).

10. The lack of widespread faculty enthusiasm for patenting and licensing is generally attributed to the fact that universities still have insufficient "incentives for the central stakeholder, the faculty member." *Id.* Promisingly, the results discussed below suggest that commercialization and traditional academic productivity may be significantly more *complementary* than the scientists interviewed for the quoted paper expect.

11. These fears are not unique to the U.S. For example, researchers who conducted a case study in Italy noted concerns about "an increasing crowding-out effect between applied activity vs. basic research . . . due to cuts in research unit budgets and increased push by governments that have obliged the researchers to collaborate with firms and external institutions for . . . funds." Mario Coccia & Secondo Rolfo, *Strategic Change of Public Research Units in Their Scientific Activity*, 28 TECHNOVATION 485, 485 (2008).

12. In doing so, it sets aside for the moment any distinction between *types of academic research*, taking all academic publications as indications of research work that is *more* inclined towards basic research than work done, e.g., explicitly within a firm out of which academic publications never arise.

13. *See, e.g.*, *Entrepreneurship at Stanford*, STANFORD NEWS (June 20, 2016), https://perma.cc/7FPD-D3ZG.

14. Washburn, *supra* note 7. University intellectual property policies like Stanford's also often reflect this sentiment with language about the university's "important role in local or national economic development." Campbell, *supra* note 6, at 83.

15. Sponsored research agreements (SRAs) are:

> contracts between a commercial entity and a university researcher to develop and commercialize a discovery. . . . SRAs benefit the university by creating interesting research opportunities for faculty and students, employment opportunities for graduates, interplay with commercial scientists, and . . . additional research funding. SRAs are an important source of university income; income from SRAs

existing law and economics literature by controlling for selection[16] and thereby accounting for the underlying factors in an individual's choices to engage in invention and disclosure.[17] Ultimately, the analysis finds that licensing significantly *increases* the number of papers[18] that a scientist publishes after making an initial invention disclosure, suggesting that the positive compensatory effects of licensing more than offset any potential adverse effects.[19]

This Note proceeds as follows. Part I provides background information on university technology transfer. Part II provides a brief review of the related literature. Part III outlines the novel data used to measure technology licenses and the data used to measure the academic output of scientist-inventors. It then also explains the empirical approach used to identify the effect of technology licensing on the academic output of scientist-inventors. Part IV describes the headline results of this empirical analysis, which suggest that licensing makes scientist-inventors *more* productive—even by traditional measures of academic productivity like scholarly publications. Finally, Part V supplements these results with additional robustness checks to allay concerns about selection and generalizability.

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exceeds that from licensing by almost 3 to 1.

Gail A. Van Norman & Roï Eisenkot, *Technology Transfer: From the Research Bench to Commercialization, Part 2: The Commercialization Process*, 2 JACC BASIC TO TRANSLATIONAL SCI. 197, 202 (2017).

16. Selection occurs when, for example, the individuals in the "treated" group or sample are not representative of the population and are, therefore, fundamentally different in some way from those in the "control" group, rendering inference about the average treatment effect problematic if not impossible.

17. *See*, *e.g.*, Jerry Thursby & Marie Thursby, *University Licensing: Harnessing or Tarnishing Faculty Research*, 10 INNOV. POL. & ECON. 159, 173 (2010) (comparing never-disclosing faculty to disclosing faculty and finding that "those who disclose are on average more productive in terms of numbers of publications than those who never disclose" and capturing not only the effect of technology transfer on productivity but also potential differences in underlying researcher ability).

18. Publication counts are a common metric of academic productivity. *See*, *e.g.*, Sharon G. Levin & Paula E. Stephan, *Research Productivity Over the Life Cycle: Evidence for Academic Scientists*, 81 AM. ECON. REV. 114 (1991). However, like any metric, publication counts are not without flaws. For example, publications may fail to capture underlying dynamics within a field relating to co-authorship, although this concern would not affect the analysis below because it would affect both licensing (i.e., treated) and non-licensing (i.e., control) inventors. Publication counts may also fail to capture the quality of the research or the broader impact of the inventor (e.g., in mentorship). Regardless, publication counts provide insight into the faculty member's research contributions in academic circles.

19. These results are robust to several econometric specifications, as discussed below, that indicate they are unlikely to be driven by selection effects.

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I. BACKGROUND ON UNIVERSITY TECHNOLOGY TRANSFER

The United States Patent and Trademark Act Amendments of 1980—colloquially known as the Bayh-Dole Act—first granted universities the right to retain title to intellectual property derived from federally funded research.[20] Historically, the federal government has funded the "majority of university [research and development (R&D)] work, reaching as high as 73 percent [of such funding] in the late 1960s."[21] Figure 1 shows the share of university science and engineering R&D funding by source from 1990 to 2017.[22] In this more recent period, federal funding consistently represented about sixty percent of total research dollars flowing into U.S. universities' science and engineering programs. Before Bayh-Dole, federally funded university-based inventions were generally "neither patented nor transferred to the commercial sector" in the U.S.[23] Thus, a change in the rights to the intellectual property arising out of federally funded projects represented a significant shift in the technology transfer landscape.

Bayh-Dole was motivated by the concern that, for example, "a candidate drug discovered in a university lab might never be picked up by a pharmaceutical firm for further development due to a lack of clarity over title and patent rights."[24] Evidence suggests that it was an impactful policy change in this regard. Following the enactment of Bayh-Dole, technology licensing from universities appears to have increased "substantially," to the benefit of local economies and universities alike.[25]

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20. 35 U.S.C. § 200-12. Historical accounts suggest that universities were "routinely claiming ownership of faculty and staff inventions and engaged in efforts to commercialize them" prior to Bayh-Dole, but only when those inventions were not federally funded. Campbell *supra* note 6, at 91; *see id.* at 98. University ownership of intellectual property has been ongoing for at least a century, as "[t]he first formal patent policies were adopted in 1924 by Lehigh University and Columbia." *Id.* at 92 (citing Archie M. Palmer, *Survey of University Patent Policies: Preliminary Report*, NAT'L RSCH. COUNCIL (1948)).

21. *R&D at Colleges and Universities*, AM. ASSOC. FOR THE ADVANCEMENT OF SCI., https://www.aaas.org/programs/r-d-budget-and-policy/rd-colleges-and-universities.

22. Data are available, *id.*, and were initially provided by *Higher Education R&D Survey Data Series*, NAT'L SCI. FOUND., https://perma.cc/9RWD-6TY2.

23. Mary Margaret Styer, Jack Kerrigan & Andy Lustig, *A Guide Through the Labyrinth: Evaluating and Negotiating a University Technology Transfer Deal*, 11 B,U. J. SCI. & TECH. L. 221, 222 (2005).

24. Lerner et al., *supra* note 4.

25. JOEL GOTKIN, THE UNITED STATES BAYH-DOLE ACT AND ITS EFFECT ON UNIVERSITY TECHNOLOGY TRANSFER 64 (2012). A recent empirical analysis by Naomi Hausman also suggests that Bayh-Dole led to faster local growth in employment, wages, and corporate innovation. Hausman, *supra* note 1. Moreover, Lynne Zucker and Michael Darby have shown that academia-industry relationships facilitate the diffusion of university-based inventions and foster collaborative relationships between academic and industry scientists that increase industry's rate of innovation. Zucker & Darby, *supra* note 1.

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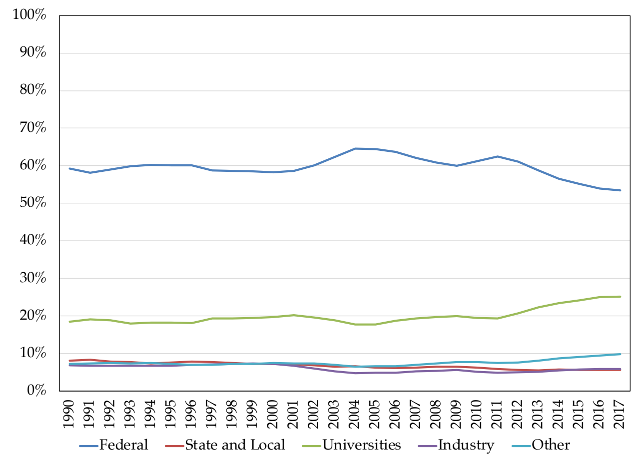
Figure 1: University Science and Engineering R&D Funding Trends



The main mechanism for technology transfer at universities today is the technology license agreement. These agreements take the form of contracts between a university and a third party (e.g., a private company or a government entity) and are similar in many ways to private-sector technology license agreements.[26] Through its licenses, the university can grant its "rights in the defined technology to a third party for a period of years," subject to certain limitations, such as field or region of use.[27] The specific terms of the agreement differ depending on the technology, the parties involved, and the university's overall licensing strategy. However, in keeping with Bayh-Dole's goal of technology diffusion for the good of society, the agreements often contain provisions "to ensure that the licensee will diligently develop the technology."[28] Notably, it is the university and not the scientist-inventor (e.g., faculty member) that generally holds the rights to the technology at issue.

26. In a technology license agreement, regardless of whether a university is involved or not, "an IP owner gives someone permission to use certain IP for a specified period of time in exchange for payments called 'royalties' or 'license fees.' . . . [O]wnership of the licensed IP is not transferred and instead only certain specified permissions regarding the IP are granted." Joseph T. Miotke, *Technology Licensing for Beginners: An Introduction*, 39 LICENSING J. 1, 1 (2019).

27. *Licensing and Negotiations*, STANFORD UNIV. OFF. OF TECH. LICENSING, https://perma.cc/2P7D-QDG7. Field of use restrictions "preclude[] licensees from operating outside of the technical field specified." Florian Schuett, *Field-of-Use Restrictions in Licensing Agreements*, 30 INT'L J. INDUS. ORG. 403, 403 (2012). Region of use restrictions operate analogously with respect to the geographic regions specified. *See id.* at 405.

28. *Licensing and Negotiations*, *supra* note 27.

In the U.S., faculty and other scientific researchers typically assign the intellectual property rights to their inventions to the university when commencing employment.[29] The policies of individual universities "vary greatly in the extent to which they claim ownership or require assignment of inventions, as well as in their overall tone and complexity."[30] However, most institutions make broad claims of ownership over all intellectual property that is "conceived or first reduced to practice in whole or in part by members of the faculty or staff (including student employees) . . . in the course of their [u]niversity responsibilities or with more than incidental use of [u]niversity resources."[31] Thus, the university, not the scientist, can assign intellectual property rights in the technology through a licensing agreement to an existing private-sector company or to a start-up.[32]

The unique landscape of university patenting and licensing poses some distinctive challenges for academic technology transfer. For reference, Figure 2 outlines a simplified case of how a university licensing process might proceed, using Stanford's process as an example.[33] One unique feature of university technology licensing is that academic scientists earn a share of the licensing revenue from their inventions, whereas inventor-employees working in the private sector generally receive no such benefit.[34] Moreover, universities face an inherent tension around

29. Unsurprisingly, conflicts around this issue have occasionally arisen between universities and faculty inventors. For example, in *Stanford v. Roche*, a Stanford research fellow's concurrent agreements to assign "his 'right, title and interest in' inventions" to Stanford *and* "his 'right, title, and interest in . . . ideas, inventions and improvements'" to a private company named Cetus during an academia-industry research collaboration led to a Supreme Court debate on the assignment and potential infringement of three patents secured by Stanford in relation to the fellow's work. *Bd. of Trs. of the Leland Stanford Junior Univ. v. Roche Molec. Sys., Inc.*, 563 U.S. 776 (2011); Sean M. O'Connor, *The Aftermath of Stanford v. Roche: Which Law of Assignments Governs?*, 24 INTELL. PROP. J. 29, 30 (2011). Ultimately, however, this case "did not fundamentally alter the national patent landscape . . . Instead, it reinforced the value of having in place strong contractual agreements between the university and its faculty researchers," which is what university scientists are generally party to today. Brian K. Krumm, *University Technology Transfer - Profit Centers or Black Holes: Moving Toward a More Productive University Innovation Ecosystem Policy*, 14 NW. J. TECH. & INTELL. PROP. 171, 177 (2016).

30. Campbell, *supra* note 6, at 81.

31. *Id.*; *Stanford Policies on Intellectual Property*, STANFORD UNIV. OFF. OF TECH. LICENSING, https://perma.cc/C3Q2-JYHY.

32. Styer, Kerrigan & Lustig, *supra* note 23, at 224.

33. In this diagram, the TTO is included as part of the university.

34. *See* Lisa Larrimore Ouellette & Andrew Tutt, *How Do Patent Incentives Affect University Researchers?*, 61 INT'L REV. L. & ECON. 1 (2020). For many university scientists, inventions are a highly intentional part of their research. For example, work on pharmaceuticals, biotechnology, and medical technology rank among the most frequently patented university inventions. *Invention: United States and Comparative Global Trends*, NAT'L SCI. FOUNDATION (2018), https://perma.cc/8XNW-MTW5. However, other university scientist-inventors may discover potentially protectable intellectual property as a

timing the patenting of these inventions relative to public disclosures that can constitute statutory bars to patenting—e.g., scientific publications and perhaps even grant proposals.[35] However, conversations with university technology transfer offices (TTOs) suggest that this tension is relatively easy for universities to navigate. Putting a patent application together is much quicker than getting a scientific paper published in an academic journal. Legal blogs, for example, periodically describe filings made "in as little as 48 hours because the inventor had submitted an academic paper to a publisher."[36] Navigating these challenges proves fruitful both for the university and the broader economy, as research suggests that patents and subsequent public disclosures are more powerful jointly, rather than individually, at "facilitating the disclosure of knowledge."[37] The question remains, however, of whether licensing benefits the scientist-inventor and scientific research more broadly, or whether commercialization simply poses an unwelcome distraction.

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byproduct of more basic scientific research agendas, which differs significantly from the approach of private-sector inventors for-hire who work on applied research and development full-time. The standard example of such accidental discovery is penicillin:

> A chance event in a London laboratory in 1928 changed the course of medicine. Alexander Fleming, a bacteriologist at St. Mary's Hospital, had returned from a vacation when, while talking to a colleague, he noticed a zone around an invading fungus on an agar plate in which the bacteria did not grow. After isolating the mold and identifying it as belonging to the Penicillium genus, Fleming obtained an extract from the mold, naming its active agent penicillin. He determined that penicillin had an antibacterial effect on staphylococci and other gram-positive pathogens.

Robert Gaynes, *The Discovery of Penicillin—New Insights After More Than 75 Years of Clinical Use*, 23 EMERGING INFECTIOUS DISEASES 849, 849 (2017). Even within applied research aimed at invention, serendipity may play an important role in discovery. Studies suggest, for example, that "the discovery of 5.8% (84/1437) of all [anticancer] drugs on the market involved serendipity." Emily Hargrave-Thomas, Bo Yu & Jóhannes Reynisson, *Serendipity in Anticancer Drug Discovery*, 3 WORLD J. CLINICAL ONCOL. 1, 1 (2012).

35. Styer, Kerrigan & Lustig, *supra* note 23.; 35 U.S.C. § 102(b); Daniel S. Hodgins & J. Michael Matula, *Government Grant Applications, Despite E. I. du Pont de Nemours v. Cetus, Are Not Necessarily Prior Art*, 74 J. PAT. & TRADEMARK OFF. SOC'Y 241 (1992); *Invention Disclosures and Status*, STANFORD UNIV. OFF. OF TECH. LICENSING, https://perma.cc/ H3ZS-UVSP.

36. *How Quickly Can You File a Patent Application?*, CHILDS PATENT LAW (Mar. 3, 2021), https://perma.cc/VBK2-ZG4F.

37. Joshua S. Gans, Fiona E. Murray & Scott Stern, *Contracting Over the Disclosure of Scientific Knowledge: Intellectual Property and Academic Publication*, 46 RSCH. POL'Y 820, 820 (2017).

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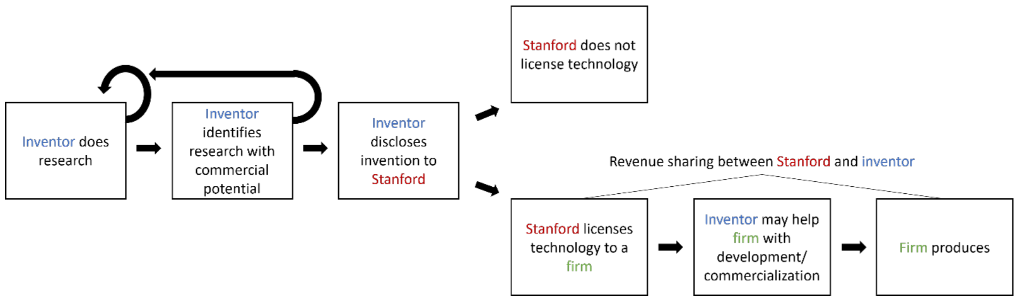
Figure 2: Simplified Licensing Process



II. RELATED LITERATURE

Scholars have already tackled theoretical questions about how university TTOs can maximize the licensing of scientists' inventions. For example, Richard Jensen and Marie Thursby have shown how including output-based payments, such as royalties, in licensing contracts can help induce scientist cooperation in commercialization.[38] The need for this type of incentive is consistent with predictions from the theoretical economics literature about multi-dimensional worker effort. Bengt Holmström and Paul Milgrom have shown that, when worker incentives are strong along one dimension, firms have to set strong incentives for effort along any other desirable dimensions that compete for the worker's effort and attention.[39] In this setting, Holmström and Migrom's reasoning would say that, because there are strong tenure returns to academic research and publications, universities must set similarly strong incentives to induce industry engagement, considering that faculty are limited by the amount of attention, time, and effort that they can expend across the various dimensions of their jobs.

The type of revenue sharing that Jensen and Thursby propose is, in fact, *required* by the Bayh-Dole Act.[40] That is to say, university scientist-inventors are legally obligated to a share of royalties. However, universities get to specify the *size* of the share.[41] Research by Lisa Larrimore Ouellette and Andrew Tutt demonstrates that the royalty-sharing policies of U.S. research universities have varied greatly across time and space.[42] Nonetheless, increasing inventors' share of royalties does not seem to have

38. Richard Jensen & Marie Thursby, *Proofs and Prototypes for Sale: The Licensing of University Inventions*, 91 AM. ECON. REV. 240 (2001).

39. Bengt Holmström & Paul Milgrom, *Multitask Principal-Agent Analyses: Incentive Contracts, Asset Ownership and Job Design*, 7 J. L., ECON. & ORGANIZATION 24 (1991).

40. 35 U.S.C. § 202(c)(7)(B).

41. *See, e.g.*, Saul Lach & Mark Schankerman, *Royalty Sharing and Technology Licensing in Universities*, 2 J. EUR. ECON. ASS'N 252 (2004).

42. Ouellette & Tutt, *supra* note 34.

a significant effect on their commercialization activity.[43] That academic scientists seem relatively unmotivated by these financial incentives raises the question of whether there are other costs that they incur during patenting and licensing that have been unobserved to law and economics researchers thus far.

For example, surveys suggest that university patenting could skew scientist research agendas toward commercial rather than academic priorities, cause article publication delays, and force scientists to re-allocate their effort, time, and attention away from other projects toward the one being licensed.[44] Too strong an emphasis on commercialization could also result in early-stage ideas reaching the private sector before it is efficient for them to do so because private-sector companies generally employ fewer scientists on a given early-stage idea "relative to what would happen in academia."[45] Therefore, despite the advantages of university licensing discussed above, "it cannot be assumed that engagement activities are always beneficial."[46]

The negative implications of over-commercialization could be profound if licensing agreements distract researchers from the basic research required to sustain economic growth. Research has shown that private-sector companies do not have the financial incentive to perform enough basic research on their own, so society relies on academic scientists to fill in the gap.[47] Basic scientific research is essential because it provides other researchers, and the world more broadly, with the building blocks and "fundamental stock of knowledge" that allow subsequent research and innovation to move forward.[48] Indeed, it is basic research that has led to many of the contemporary "innovations that have improved the country's productivity and quality of life."[49] Law and economics scholars thus generally refer to basic research as having large "social returns" on investment.[50] Therefore, if tasks related to licensing an invention distract a

43. *Id.* Indeed, other research suggests that professors prefer sponsored research in license agreements to royalty and equity payments alone. Jensen & Thursby, *supra* note 38.

44. *E.g.*, Eric Campbell et al., *Data Withholding in Academic Genetics: Evidence from a National Survey*, 287 J. AM. MED. ASS'N 473 (2002).

45. Philippe Aghion, Mathias Dewatripont & Jeremy Stein, *Academic Freedom, Private-Sector Focus, and the Process of Innovation*, 39 RAND J. ECON. 617, 619 (2004).

46. Markus Perkmann et al., *Academic Engagement and Commercialisation: a Review of the Literature on University-Industry Relations*, 42 RSCH. POL'Y 423, 432 (2013).

47. *E.g.*, Ufuk Akcigit, Douglas Hanley & Nicolas Serrano-Velarde, *Back to Basics: Basic Research Spillovers, Innovation Policy, and Growth*, 88 REV. ECON. STUD. 1 (2020); U.S. Cong., Joint Econ. Comm., *supra* note 8.

48. U.S. Cong., Joint Econ. Comm., *supra* note 8.

49. *Id.*

50. *See*, *e.g.*, INT'L MONETARY FUND, WORLD ECONOMIC OUTLOOK: RECOVERY DURING A PANDEMIC 65-82 (2021); Benjamin F. Jones & Lawrence H. Summers, *A Calculation of the Social Returns to Innovation* in INNOVATION AND PUBLIC POL'Y (Austan Goolsbee & Benjamin F. Jones eds., 2021). The social return on investment perspective allows for the quantification of "the value created by a program[] . . . beyond financial value. It incorporates social, health, environmental, and economic costs and benefits" of a

basic scientist from their research, these social returns may not be realized. In the extreme, if industrial tasks were to be pursued *en masse* by university scientists, "the further progress of industrial development would eventually stagnate if basic scientific research were long neglected."[51] Thus, research suggests that too much university-industry collaboration could have adverse effects on economy-wide innovation and long-term growth.

However, the empirical analysis discussed below suggests that a successful license significantly *increases* the number of papers that a scientist publishes in subsequent years. This Note also shows that controlling for concerns about selection (i.e., that licensing is endogenous to the invention's quality or the inventor's aptitude) does not change the empirical findings.[52] These conclusions are consistent with the hypothesis that positive outcomes of commercialization like sponsored research and industry collaborations—either to develop existing inventions further or to lead to new technologies—can offset the costly aspects of the technology transfer process such that researcher output increases overall.

This Note is the first to examine the effect of *licensing* on academic publication rates in a large U.S. university. Existing research by Pierre Azoulay, Waverly Ding, and Toby Stuart examines the influence of *patenting* on the rate, quality, and content of public research outputs among academic life scientists.[53] However, the data here suggest that productivity gains are attributable not to patenting alone but rather to industry engagement arising out of licensing and commercialization.[54] In the data sample analyzed in this Note, ninety percent of inventors who never had a technology

program, funding recipient, or policy. *Appendix: Social Return on Investment (SROI) Methodology and Sensitivity Analysis of the Case Studies*, UNITED NATIONS DEVELOPMENT PROGRAMME,.

51. VANNEVAR BUSH, OFF. SCI. RSCH. & DEVELOPMENT, SCIENCE: THE ENDLESS FRONTIER 17 (1945).

52. Several unsuccessful attempts to identify a statistical instrument that is a significant predictor of licensing—e.g., using the length of marketing abstracts as in work by Weixin Liang et al. or using journals associated with successful licensing—support OTL statements that it is not feasible to predict *ex ante* which inventions will be licensed. Weixin Liang et al., *Systematic Analysis of 50 Years of Stanford University Technology Transfer and Commercialization*, 3 PATTERNS 1 (2022).

53. Pierre Azoulay, Waverly Ding & Toby Stuart, *The Impact of Academic Patenting on the Rate, Quality and Direction of (Public) Research Output*, 57 J. INDUS. ECON. 637 (2009). The authors' conclusions in this paper also extend previous smaller-sample evidence. *E.g.*, Ajay Agrawal & Rebecca Henderson, *Putting Patents in Context: Exploring Knowledge Transfer from MIT*, 48 MGMT. SCI. 44 (2002); Kira Fabrizio & Alberto Di Minin, *Commercializing the Laboratory: Faculty Patenting and the Open Science Environment*, 37 RSCH. POL'Y 914 (2008).

54. Moreover, the authors use an inverse probability of treatment weight to account for the dynamics of self-selection into patenting. In contrast, this Note's approach directly controls for such dynamics by focusing exclusively on academic scientists who disclose inventions and then following whose technologies either do or do not get licensed.

disclosure successfully licensed still had at least one of their technologies patented.[55] Moreover, intellectual property generated by university researchers is not always patentable; for example, "software code" may instead be transferred through copyright licensing.[56] Therefore, focusing on licensing rather than patenting helps uncover the changes in academic productivity attributable to commercialization more precisely.

Other related research considers the effects of university technology transfer on academic productivity in non-U.S. settings. However, this work has fueled rather than resolved the debate about the net effect of university commercialization. Some papers in this literature suggest that academic research groups can "develop[] a record of applied publications without affecting their basic research publications," while others express concerns that a "stronger emphasis on partnerships of university scientists with the private sector is significantly undermining the ability of the higher education sector to generate new ideas."[57]

Although a complete review of the economics and business literatures on university commercialization is beyond the scope of this Note, other work in this area investigates, *inter alia*, topics such as the effect of national policies on universities' technical efficiency; the effect of licensing on journal citations to academic publications; and the effect of super-star scientists on the direction of scientific research.[58] In addition to these academic debates, policymakers have taken on government projects to design optimal incentive structures for the diffusion of university-based inventions—e.g., annual benchmarking reports on "European Competitiveness and Industry," which assess the structure of industry-science relations in Europe and recommend areas for improvement.[59] Therefore, the findings of this Note are relevant not only to the law and economics literatures on innovation and intellectual property but also to governments hoping to improve national growth rates through innovative academic research.

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55. The rate of patenting in the treated group, defined for the sake of this analysis as inventors who licensed their first disclosure, is slightly higher at ninety-five percent.

56. *Copyright*, STANFORD UNIV. OFF. OF TECH. LICENSING, https://perma.cc/5JGE-YQLV.

57. Liana Ranga, Koenraad Debackere & Nick Tunzelmann, *Entrepreneurial Universities and the Dynamics of Academic Knowledge Production: A Case Study of Basic vs. Applied Research in Belgium*, 58 SCIENTOMETRICS 301, 301 (2003); Viktoriya Galushko & Ken Sagynbekov, *Commercialization of University Research in Canada: What Can We Do Better?*, 5 INT'L J. BUS. ADMIN. 1, 12 (2014).

58. Jaepil Han, *Effects of Technology Transfer Policies on the Technical Efficiency of Korean University TTOs*, 40 KDI J. ECON. POL'Y 23 (2019); Neil Thompson, Arvids Ziedonis & David Mowery, *University Licensing and the Flow of Scientific Knowledge*, 47 RSCH. POL'Y 1060 (2018); Pierre Azoulay, Christian Fons-Rosen & Joshua S. Graff Zivin. *Does Science Advance One Funeral at a Time?*, 109 AM. ECON. REV. 2889 (2019).

59. *See* Wolfgang Polt et al., *Benchmarking Industry-Science Relations - The Role of Framework Conditions*, 28 SCI. & PUB. POL'Y 247 (2001).

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III. DATA AND RESEARCH DESIGN

This Note uses Web of Science (WoS) data to measure academic publications. WoS is a publisher-independent global citation database that records detailed information about almost 1.9 billion cited references.[60] The data include publication records, journal information, and citations for more than 64,000 distinct authors affiliated with Stanford.[61] Thus, the analysis discussed below is able to observe academic research output for a comprehensive set of Stanford-affiliated scientists over time.

In order to identify the set of Stanford scientists who are also inventors, this Note also utilizes new data from the Stanford Office of Technology Licensing (OTL) that details all inventions disclosed to Stanford after 2000, along with information about whether each technology was marketed, licensed, or patented.[62] The OTL data are linked to the WoS database by name.[63] The final data sample includes about 2,700

60. This Note's version of the data begins before 1970 and is complete through the end of 2018.

61. Author affiliations are identified by email domain—for example, extracting Stanford from [scholar_name]@stanford.edu. The relevant set of authors is identified using this approach, and then all of their relevant publications are retrieved, regardless of publication-level affiliation. For a more extensive discussion of this methodology, see Lerner et al., *supra* note 4, at 13 (explaining that "[f]or each author of each publication in the Web of Science data, we extract the listed e-mail address where available. Because no more than one e-mail address is listed for each author, this provides a solution to the multiple affiliations problem described above. For each e-mail address, we extract the domain—for example, extracting 'dartmouth' from heidi.lie.williams@dartmouth.edu"). Authors with a stanford.edu email domain include those affiliated with the University, Stanford Medicine, the SLAC National Accelerator Laboratory and other associated research institutes.

62. Stanford's patent policy requires that potentially patentable inventions be disclosed on a timely basis. As discussed above, this helps ensure that academic publications and other public disclosures do not bar patenting. The raw OTL dataset includes approximately 10,000 disclosed inventions after 2000, corresponding to over 11,000 distinct inventors. The analysis discussed below considers inventions disclosed between 2001 and 2013 and papers published between 1996 and 2018.

63. Approximately 6,000 inventors are matched between the OTL and WoS datasets. There are three main explanations for unmatched inventors: (i) they never published a paper that is observable in the WoS data; (ii) they never published a paper while affiliated with Stanford; and (iii) their name is incomplete in the WoS data—e.g., first initial only. These issues are common to other research that link to the WoS disambiguated names from other datasets. This Note focuses its analysis on inventors who either had their first disclosure licensed or who never had a license successfully negotiated for any of their technologies. This approach improves the validity of the consistency assumption that is necessary for an empirical analysis using a difference-in-difference specification—i.e., there are no different forms of treatment with different potential outcomes together in the treatment group. However, the downsides of this approach include a smaller sample size that may miss some observations with heterogeneous effects. About 5,200 inventors meet these criteria in the post-2000 period. The data sample that this Note focuses on below for the regression analysis limits the data further to first disclosures occurring between 2001

Stanford inventors, approximately thirty percent of whom had at least one license successfully negotiated through the OTL.

Using these data, this Note estimates the treatment effect of licensing on an inventor's rate of academic publication for each year after a disclosure.[64] Each year-specific treatment effect represents how many additional (or fewer) articles a given Stanford scientist published on average because of their commercialization activity—i.e., that would not have happened but-for a successful technology license.

For the reasons discussed above, one could theoretically expect the treatment effect of licensing on academic productivity to be either positive or negative. If the inventor's commercialization effort comes at the significant expense of academic research effort, for example, the net effect of licensing on academic productivity could be negative. However, if benefits like sponsored research and industry collaborations

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and 2013 (inclusive) in order to ensure that the analysis can observe post-licensing publications for several years following the disclosure. The effects of licensing on academic output in research publications may take time to manifest because both research and publication can be time-consuming.

64. This analysis is always conditional on disclosure and uses the following difference-in-difference panel regression to estimate the yearly treatment effect:

$$y_{i,t} = \alpha_0 + \sum_{j=-5}^{5} \left[\gamma_j \mathbb{I}_{i,t}^{j\text{ Years Post}} + \beta_j\left(\mathbb{I}_{i,t}^{j\text{ Years Post}} \times \mathbb{I}_{i}^{\text{Treat}}\right)\right] + \omega_1 \text{Age}_{i,t} + \omega_2 \text{Age}_{i,t}^2 + \theta_i + \eta_t + \varepsilon_{i,t},$$

where $y_{i,t}$ is the number of publications by inventor i in year t, $\mathbb{I}_{i,t}^{j\text{ Years Post}}$ is an indicator for $t = j$ years after i's first disclosures, $\text{Age}_{i,t}$ is the number of years that have passed in year t since i's first academic publication, θ_i is an inventor fixed effect, η_t is a publication year fixed effect, and $\mathbb{I}_{i}^{\text{Treat}}$ is an indicator for treated inventors. Treated inventors $\left(\mathbb{I}_{i}^{\text{Treat}} = 1\right)$ are defined as inventors who had their first disclosure successfully licensed. Control inventors $\left(\mathbb{I}_{i}^{\text{Treat}} = 0\right)$ are defined as inventors who never had a disclosure licensed. Each year-specific treatment effect, β_j, represents the average number of additional (or fewer) publications made j years after disclosure by treated inventors relative to control inventors. This economic specification requires several assumptions for the treatment effect of licensing to be causally identified. First, the probability of licensing an invention that is disclosed must lie between zero and one, not inclusive. Interviews with TTOs around the country confirm that they expect only a minority of inventions to ultimately be licensed but that predicting *ex ante* which ones will be licensed is impossible in practice. Second, without licensing, the difference in publication rates between the "treated" and "control" groups must be constant. Figure 3 shows parallel trends in the pre-period that support this assumption. Third, publication rates should not be affected by others' licensing behavior. This analysis controls for the possibility that one scientist's research productivity changes because of another's licensing behavior below by analyzing spillovers, which suggest that the baseline treatment effect estimate is conservative. Lastly, for each researcher, there should be no different forms or versions of licensing that lead to different treatment effects. As discussed above, this Note's analysis mitigates such concerns by focusing only on treated inventors who had their first disclosure licensed rather than including potentially heterogeneous treatments in the form of inventors who already have strong industry relationships through past licenses.

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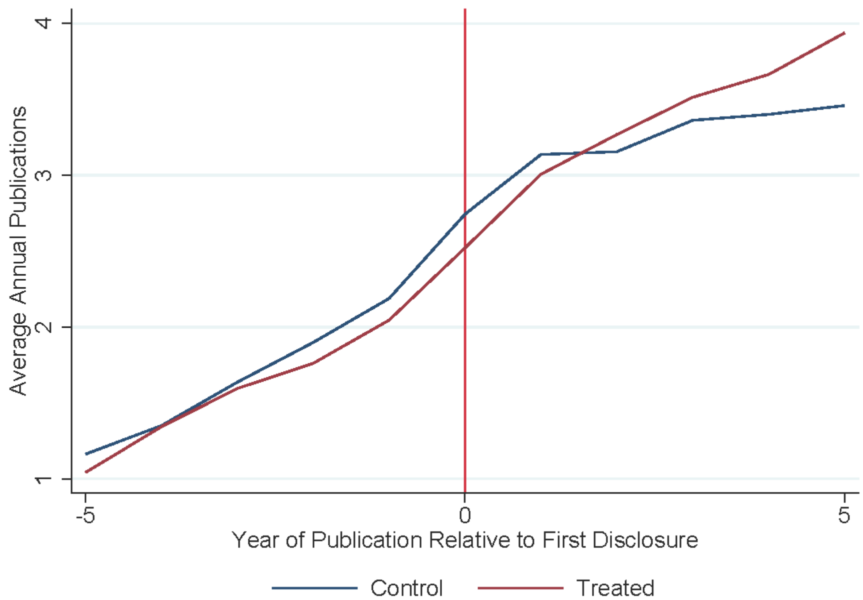
enable the inventor to be *more* productive, then the net effect of licensing on academic productivity could be positive. Both channels may be active in this setting, so the net effect is *a priori* ambiguous. Figure 3 suggests that academic scientists who successfully license a disclosure (in red) publish more papers than their peers who do not license a disclosure (in blue). This relatively naïve descriptive evidence is consistent with the results of the more robust econometric analysis presented below.

Figure 3: Publication Trends (Raw Data)



The more sophisticated econometric approach employed below mitigates concerns that licensing is endogenous to the quality of the inventor. These steps blunt any effect of systematic differences between inventors—e.g., that treated inventors are simply smarter or somehow better at both conducting publishable research and inventing licensable technologies—in two key ways. First, the estimation only considers scientists at Stanford who disclose inventions to the OTL; this minimizes any bias that might arise in an estimation across all Stanford scientists due to the fact that some scientists select into invention while others do not. That all scientist-inventors in the sample are Stanford researchers who successfully completed research and found a promising invention that they believed was worth disclosing also decreases potential heterogeneity in the estimated treatment effect.[65] Second, the analysis isolates the changes in publication rates that occur for each individual scientist only, not across

65. Regardless of their subsequent licensing outcomes, almost all disclosures in this sample were also patented by the Stanford OTL, as discussed *supra* note 54.

different scientists.[66] Focusing on the "within subject" treatment effect avoids mistakenly attributing confounding factors that do not vary over time (e.g., inherent intelligence or research productivity) to the effect of *licensing*. This Note also includes alternative empirical specifications and placebo tests below to further allay selection concerns.[67]

IV. EMPIRICAL RESULTS

This empirical analysis suggests that licensing is associated with an *increase* in subsequent academic publications at Stanford (conditional on disclosing an invention). Moreover, the positive effect increases over time after a disclosure. As shown in Figure 4 and detailed in Appendix Table 1, inventors who successfully license their first disclosure publish approximately 0.6 additional papers on average in the fifth year after disclosure compared to control inventors without successful licenses.[68] Each point estimate of the average treatment effect is represented by a dot in Figure 4. The standard errors are represented by the lines above and below each point estimate.[69] This average treatment may seem like a small change but actually represents a twenty-six percent increase in average annual publications (off of a base rate of approximately 2.3 papers published per year).[70]

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66. To achieve this, the econometric specification includes inventor-level fixed effects to account for constant unobserved heterogeneity across inventors. Including inventor-level fixed effects helps account for scientist quality by isolating "the variation that occurs *within*" each inventor. Nick Huntington-Klein, *Fixed Effects*, THE EFFECT: AN INTRODUCTION TO RESEARCH DESIGN AND CAUSALITY (2021), https://perma.cc/5VUK-EL8J. Said differently, inventor-level quality should not affect the estimated treatment effect of licensing here because "fixed effects models eliminate time-invariant confounding, estimating an independent variable's effect using only within-unit variation." Jonathan Mummolo & Erik Peterson, *Improving the Interpretation of Fixed Effects Regression Results*, 6 POL. SCI. RSCH. & METHODS 829, 829 (2018).

67. In statistical analysis, a placebo test "refers to a type of auxiliary analysis where the researcher checks for an association that should be absent if the assumptions underlying the design hold but might be present if those assumptions are violated in some relevant way." Andrew C. Eggers, Guadalupe Tuñón & Allan Dafoe, *Placebo Tests for Causal Inference*, 68 AM. J. POL. SCI. 1106, 1106 (2024). The assumption being tested below is that the uptick in subsequent publications visible for treated scientist-inventors is attributable to their commercialization activity rather than to underlying differences in researcher quality.

68. The average license is negotiated about two years after the initial disclosure. This Note focuses on the disclosure date rather than the licensing date as the treatment date in the empirical analysis to avoid specifying arbitrary hypothetical licensing dates for control inventors. It is also not obvious that inventor engagement with an industry firm would occur exclusively after licensing, whereas it would likely occur only after disclosure.

69. This analysis uses heteroskedasticity-robust standard errors.

70. As additional support for the robustness of this result, this Note also considers bootstrapped standard errors. To calculate bootstrapped standard errors, one "resamples

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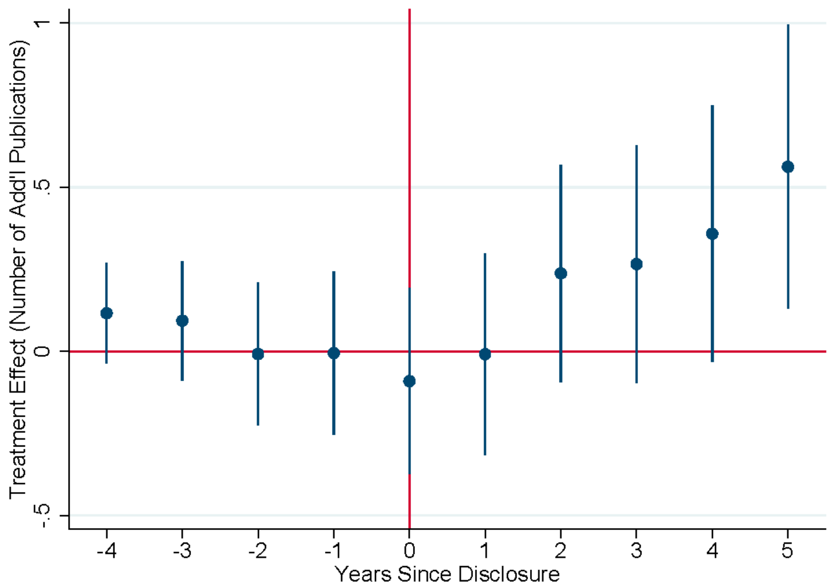
Figure 4: Average Treatment Effect Estimates



Some effects of licensing may also flow to other researchers in the licensing inventor's professional network. For example, sponsored research dollars or new ideas resulting from industry collaborations may affect other researchers' potential productivity levels. Quantifying such spillovers is essential because, if the average treatment effect estimated above is merely being driven by *negative* spillover effects onto non-licensing (control) inventors, then the true net effect of university licensing may not be positive after all.[71] Therefore, this Note tests for the spillover effects of one scientist's licensing on other scientists' productivity levels by using coauthor relationships in the WoS data.[72]

a single dataset to create many simulated samples." Trist'n Joseph, *Bootstrapping Statistics. What It Is and Why It's Used*, MEDIUM (Jun. 17, 2020), https://perma.cc/W9RU-52CH. Although there is no reason to suspect the computed standard errors presented above are unstable, bootstrapped standard errors are a helpful check on the stability of the standard error estimates because "the bootstrap can provide more accurate inferences when the data are not well behaved or when the sample size is small." Morten Hjorth-Jensen, *Resampling Techniques, Bootstrap and Blocking*, ADVANCED TOPICS IN COMPUTATIONAL PHYSICS (2021), https://perma.cc/XG4G-2Z6B. Adopting this approach instead of the method used for the headline results does not affect the headline results.

71. This might occur, for example, if the inventor is taken away from their department or collaborative projects in a way that substantially harms the ability of other scientists at the school to be productive.

72. Co-authorships here are likely close professional relationships because all authors are Stanford-affiliated.

The estimated spillover effects of licensing on otherwise untreated coauthors are positive and, in fact, even larger than the direct effects on treated inventors themselves.[73] This result could be explained by positive spillovers (e.g., influxes of fungible research money) that increase coauthors' research productivity without necessitating a shift in their time and effort towards the non-academic tasks that are required of the licensing scientist.[74]

These positive spillover effects bias the estimated average treatment effect from the baseline specification *down*. Thus, re-estimating the average treatment effect while correcting for spillovers (i.e., while excluding control inventors who had treated coauthors) yields an even larger positive estimated average treatment effect of approximately 0.7-0.8 additional papers per year by the fifth year after disclosure.[75] These highly similar results render the headline takeaways from above unchanged. The following section provides additional robustness checks on this analysis, all of which support the idea that the positive estimated effects are attributable to commercialization activities and not to underlying differences in researcher quality.

V. ROBUSTNESS CHECKS

A. Placebo Test for Selection Effects

Additional tests can be used to determine whether the treatment effects identified above are driven by licensing or by underlying inventor quality differences. For example, inventors' years of disclosure can be randomized as a placebo test.[76] Suppose

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73. *See* Appendix Figure 6. One should note, however, that the parallel trends assumption holds less well for the estimated spillover effects. The parallel trends assumption describes the difference-in-difference condition that "in the absence of the treatment, the average outcome for the treated and comparison groups would have evolved in parallel." Michelle Marcus & Pedro H. C. Sant'Anna, *The Role of Parallel Trends in Event Study Settings: An Application to Environmental Economics*, 8 J. ASS'N ENV'T & RES. ECONOMISTS. 235, 236 (2021).

74. For example, collaboration on research has "steadily increased in all fields over the past century." Austin J. Parish, Kevin W. Boyack & John P. A. Ioannidis, *Dynamics of Co-Authorship and Productivity Across Different Fields of Scientific Research*, 13 PLOS ONE 1, 2 (2018). Research dollars that one scientist receives and funnels into such collaborative projects—either directly or indirectly through inputs like graduate student time and lab resources—would be expected to increase the productivity of that project, including all its principal investigators. However, collaborators on this project would not have any obligation to increase the time that *they* spend on industry tasks because they are not involved in the licensed technology. Only the licensing scientist-inventor would have this potential distortion in time and effort.

75. *See* Appendix Figure 7.

76. Placebo disclosure years were generated in Stata by drawing a random number from a uniform distribution over (0, 13) and adding this to 2000.5 before rounding to the nearest integer.

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that the average treatment effect estimated above is simply attributable to underlying differences in inventor quality. In that case, one should expect to see randomized arbitrary ("placebo") dates of invention disclosure yielding similar estimates to those from the baseline specification. Figure 5 compares the placebo and actual (observed) results from above.[77] If the difference in publication trends captured by the estimated treatment effect is attributable solely to inventor quality, one would expect to see the lefthand panel mirror the righthand panel of Figure 5.[78] Instead, the uptick in year-specific treatment effects following the intervention completely disappears in the lefthand panel. This comparison suggests that disclosure dates *are* highly relevant to this analysis and that the effect is unlikely to be driven by fundamental differences (e.g., in quality) between the treatment and control groups.

B. Grants as a Measure of Quality

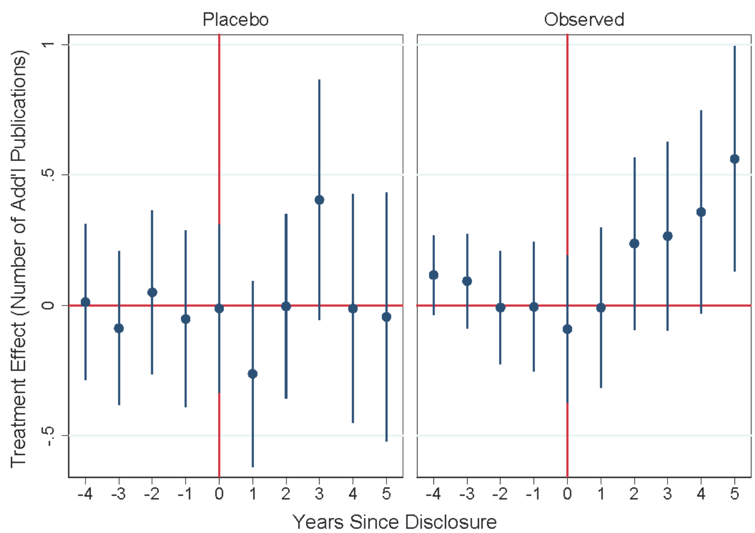
To a similar end, this Note also considers whether the treatment effect is predominantly associated with characteristics that correlate with quality. If the average treatment effect occurs primarily within observably high-quality inventors, one's skepticism about whether licensing actually drives the estimated effect should be heightened. Federal research grants are one plausible signal of high-quality inventors. Accordingly, data on both active and expired grant awards to Stanford-affiliated researchers were retrieved from the National Institutes of Health (NIH) since 1985, the Department of Energy (DOE) since 1987, and the National Science Foundation (NSF) since 1976. In 2017, these agencies accounted for approximately forty-four percent of total federal research and development funding. Grant recipients were then matched by name to inventors from the intersection of the WoS and Stanford OTL data.

Running the analysis described above separately for scientists who received grants prior to their invention disclosures and scientists who did not shows that the increase in publications induced by licensing is driven predominantly by inventors who were not named in NIH, DOE, or NSF grants prior to disclosure. This suggests that the positive treatment effect discussed above is not merely driven by selection on quality—at least as can be measured by observable metrics like grants.

77. Appendix Figure 8 compares the placebo and observed results for the specification when excluding control observations affected by spillovers.

78. The righthand panel of Figure 5 replicates the Figure 4 above.

Figure 5: Comparison with Placebo Treatment Effect Estimates



CONCLUSION

In summary, despite concerns about shifting researcher effort away from academic work, observable measures of academic productivity suggest that there are significant compensatory positive effects of university technology licensing that, on average, more than offset the impacts of effort and time reallocation. These gains are attributable not to patenting alone but rather to the industry engagement that arises out of licensing and commercialization. Although extensive analysis of the mechanisms contributing to this increase in academic research productivity is beyond the scope of this Note, likely candidates include "industry contacts [that] become sources of ideas for new research projects"[79] and sponsored research.[80] These results suggest that, at least at Stanford's current levels of technology transfer, academic productivity is not being harmed by scientists' licensing activities. This Note is also the first to suggest that these types of industry engagements have spillover effects onto other faculty, meaning that related estimates in the existing literature may underestimate the positive effects of the industry relationships of a given scientist.

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79. Azoulay, Ding & Stuart, *supra* note 53, at 641; Agrawal & Henderson, *supra* note 53, at 58 (quoting an electrical engineering and computer science professor as saying that "it is useful to talk to industry people with real problems because they often reveal interesting research questions").

80. Christopher D. Flanagan et al., *Academic Productivity Metrics Correlate Positively with Industry Funding Amongst Orthopedic Shoulder and Elbow Surgeons*, 7 JSES INT'L 372 (2023).

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It is important to bear in mind, though, that Stanford is already a high performer in terms of licensing.[81] To the extent that one might expect licensing to exhibit diminishing positive returns in terms of academic productivity gains, these results may be generalizable to other U.S. universities that are not doing as much licensing as Stanford. However, it is less clear whether these results are generalizable to licensing outside of a high-tech hub like Silicon Valley, both in terms of feasibility and in terms of equivalent enhancements to academic productivity.[82]

Important questions for future research remain about potential heterogeneity in these effects—e.g., whether there are some universities or scientists for whom licensing has a net negative impact on academic research output. Additionally, despite diligent steps to control for selection, this Note cannot completely rule out unobserved heterogeneity across licensing and non-licensing inventors; additional research that can definitively rule out such confounds would be valuable. Nonetheless, these results are a promising indication for the complementarity of academic research and technology transfer.

81. For evidence of this phenomenon, *see* NAT'L. ACAD. OF INVENTORS, TOP 100 U.S. UNIVERSITIES GRANTED U.S. UTILITY PATENTS (2022).

82. Some universities do not have as supportive commercial ecosystems in the local community. *See* TEX. HIGHER EDUC. COORDINATING BD., FROM INSIGHTS TO IMPACT: FOSTERING INNOVATION THROUGH TEXAS HIGHER EDUCATION (2024) (noting that "even though Texas may be creating many companies with IP from its higher education institutions, it is not retaining those companies in the state.").

STRIKING THE BALANCE

APPENDIX

Figure 6: Comparison of Average Treatment Effect Estimates

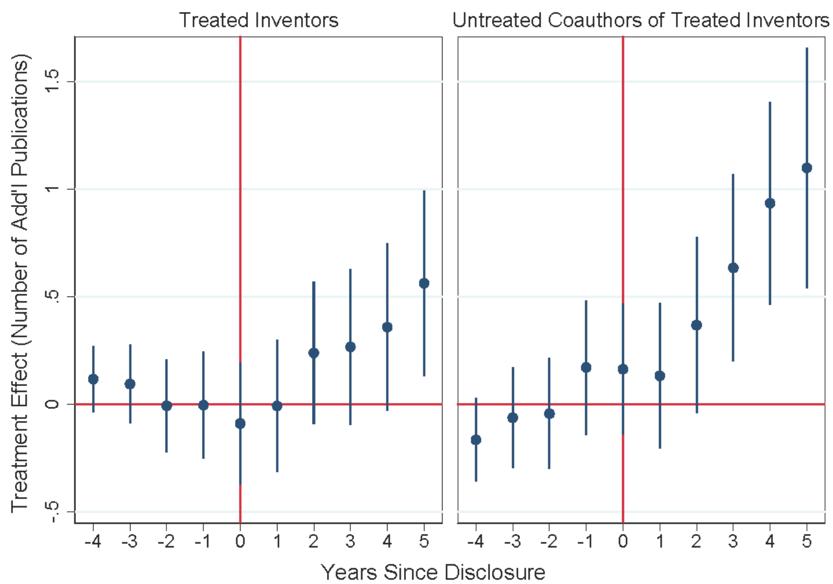

Figure 7: Comparison of Average Treatment Effect Estimates

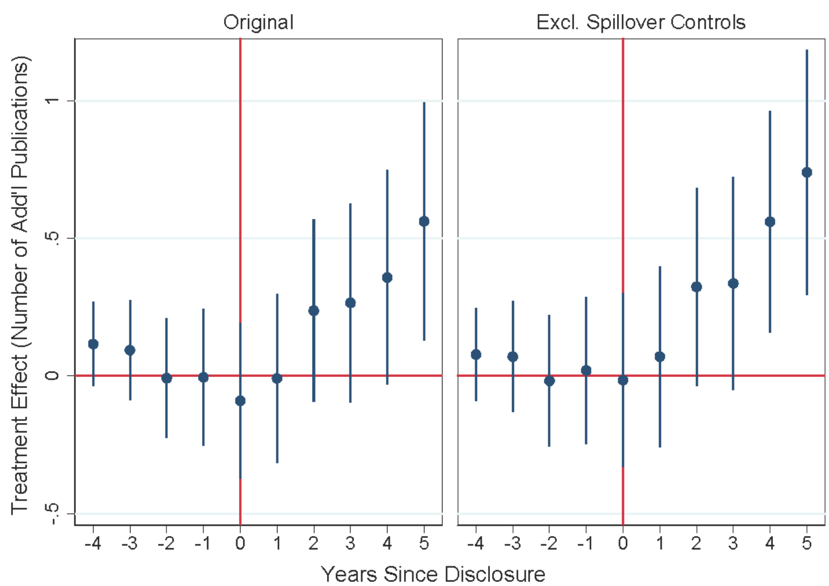

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Figure 8: Comparison with Placebo Treatment Effect Estimates

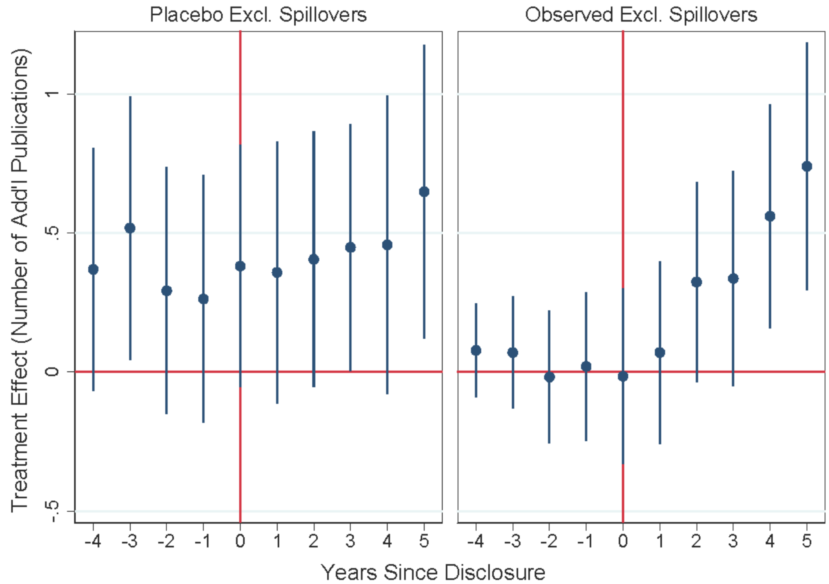
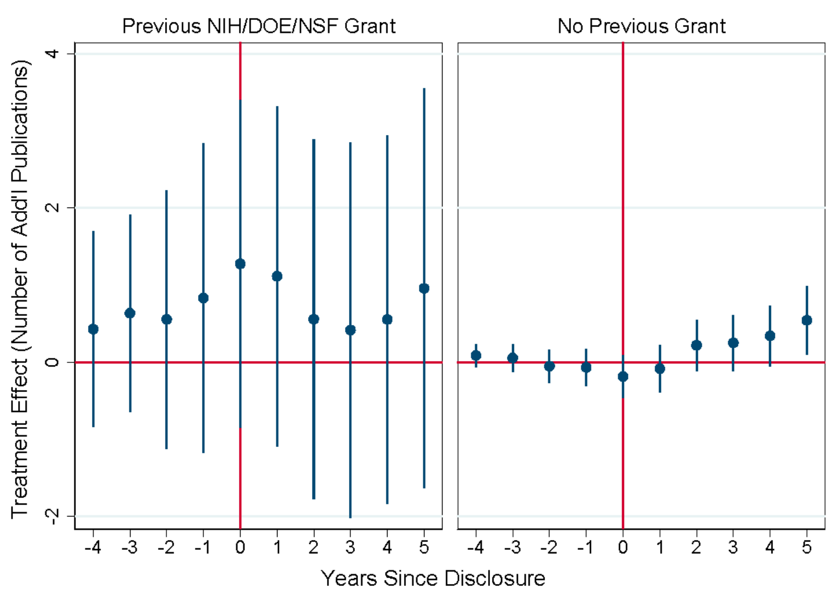


Figure 9: Treatment Effect by Grants



STRIKING THE BALANCE

Table 1: OLS Regression Results

	(1)	(2)	(3)	(4)	(5)
4 Years Before Disclosure	0.188***	0.188***	0.153***	0.153***	0.109**
	(0.0475)	(0.0475)	(0.0483)	(0.0489)	(0.0499)
3 Years Before Disclosure	0.474***	0.474***	0.401***	0.413***	0.322***
	(0.0579)	(0.0579)	(0.0580)	(0.0648)	(0.0658)
2 Years Before Disclosure	0.736***	0.736***	0.620***	0.654***	0.512***
	(0.0696)	(0.0696)	(0.0705)	(0.0828)	(0.0851)
1 Year Before Disclosure	1.026***	1.026***	0.862***	0.910***	0.714***
	(0.0764)	(0.0764)	(0.0770)	(0.0965)	(0.0994)
Year of Disclosure	1.581***	1.581***	1.367***	1.445***	1.192***
	(0.0957)	(0.0957)	(0.0958)	(0.120)	(0.122)
1 Year After Disclosure	1.974***	1.974***	1.706***	1.810***	1.499***
	(0.0977)	(0.0977)	(0.0995)	(0.132)	(0.135)
2 Years After Disclosure	1.992***	1.992***	1.668***	1.801***	1.429***
	(0.102)	(0.102)	(0.109)	(0.145)	(0.151)
3 Years After Disclosure	2.199***	2.199***	1.818***	1.999***	1.568***
	(0.107)	(0.107)	(0.125)	(0.159)	(0.172)
4 Years After Disclosure	2.238***	2.238***	1.802***	2.070***	1.581***
	(0.118)	(0.118)	(0.152)	(0.173)	(0.196)
5 Years After Disclosure	2.296***	2.296***	1.805***	2.148***	1.601***
	(0.121)	(0.121)	(0.165)	(0.178)	(0.210)
Treated x 4 Years Before Disclosure	0.114	0.114	0.114	0.117	0.116
	(0.0779)	(0.0779)	(0.0779)	(0.0779)	(0.0780)
Treated x 3 Years Before Disclosure	0.0790	0.0790	0.0782	0.0964	0.0937
	(0.0929)	(0.0929)	(0.0927)	(0.0926)	(0.0925)
Treated x 2 Years Before Disclosure	-0.0168	-0.0168	-0.0176	-0.00423	-0.00811
	(0.111)	(0.111)	(0.111)	(0.111)	(0.111)
Treated x 1 Year Before Disclosure	-0.0220	-0.0220	-0.0217	-0.00136	-0.00516
	(0.128)	(0.128)	(0.128)	(0.126)	(0.126)
Treated x Year of Disclosure	-0.101	-0.101	-0.101	-0.0856	-0.0904
	(0.145)	(0.145)	(0.145)	(0.144)	(0.144)
Treated x 1 Year After Disclosure	-0.00922	-0.00922	-0.00920	-0.00270	-0.00857
	(0.157)	(0.157)	(0.157)	(0.156)	(0.156)
Treated x 2 Years After Disclosure	0.234	0.234	0.232	0.246	0.238
	(0.169)	(0.169)	(0.169)	(0.168)	(0.168)
Treated x 3 Years After Disclosure	0.272	0.272	0.269	0.277	0.266
	(0.185)	(0.185)	(0.185)	(0.184)	(0.184)
Treated x 4 Years After Disclosure	0.384*	0.384*	0.379*	0.372*	0.358*
	(0.198)	(0.198)	(0.198)	(0.198)	(0.199)
Treated x 5 Years After Disclosure	0.599***	0.599***	0.593***	0.577***	0.562**
	(0.220)	(0.220)	(0.220)	(0.220)	(0.220)
Age			0.0980***		0.110***
			(0.0241)		(0.0250)
Age Squared			-0.00132***		-0.00137***
			(0.000361)		(0.000365)
1.treated	-0.121				
	(0.120)				
Constant	1.163***	1.127***	0.671***	1.129***	0.524*
	(0.0748)	(0.0506)	(0.198)	(0.207)	(0.297)
Inventor FE		X	X	X	X
Publication Year FE				X	X
Observations	30,008	30,008	30,008	30,008	30,008
R-squared	0.037	0.101	0.103	0.105	0.106
Number of Inventors	2,728	2,728	2,728	2,728	2,728

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 2: Spillover Regression Results

	(1)	(2)	(3)	(4)	(5)
4 Years Before Disclosure	0.337***	0.337***	0.245***	0.354***	0.254***
	(0.0888)	(0.0888)	(0.0897)	(0.0932)	(0.0938)
3 Years Before Disclosure	0.498***	0.498***	0.301***	0.500***	0.297**
	(0.104)	(0.104)	(0.106)	(0.119)	(0.119)
2 Years Before Disclosure	0.726***	0.726***	0.411***	0.708***	0.394***
	(0.109)	(0.109)	(0.114)	(0.140)	(0.142)
1 Year Before Disclosure	0.823***	0.823***	0.376***	0.766***	0.335**
	(0.109)	(0.109)	(0.120)	(0.160)	(0.165)
Year of Disclosure	0.998***	0.998***	0.413***	0.895***	0.347*
	(0.109)	(0.109)	(0.128)	(0.181)	(0.190)
1 Year After Disclosure	1.264***	1.264***	0.532***	1.108***	0.440**
	(0.115)	(0.115)	(0.145)	(0.206)	(0.218)
2 Years After Disclosure	1.378***	1.378***	0.489***	1.171***	0.382
	(0.149)	(0.149)	(0.179)	(0.244)	(0.256)
3 Years After Disclosure	1.422***	1.422***	0.374*	1.130***	0.220
	(0.146)	(0.146)	(0.193)	(0.259)	(0.277)
4 Years After Disclosure	1.422***	1.422***	0.213	1.071***	0.0408
	(0.158)	(0.158)	(0.214)	(0.266)	(0.289)
5 Years After Disclosure	1.557***	1.557***	0.187	1.119***	-0.0277
	(0.172)	(0.172)	(0.240)	(0.244)	(0.285)
Treated x 4 Years Before Disclosure	-0.233**	-0.233**	-0.208**	-0.178*	-0.167*
	(0.0979)	(0.0979)	(0.0982)	(0.0984)	(0.0985)
Treated x 3 Years Before Disclosure	-0.199*	-0.199*	-0.143	-0.0916	-0.0635
	(0.119)	(0.119)	(0.119)	(0.119)	(0.119)
Treated x 2 Years Before Disclosure	-0.239*	-0.239*	-0.146	-0.0967	-0.0447
	(0.128)	(0.128)	(0.129)	(0.131)	(0.131)
Treated x 1 Year Before Disclosure	-0.0744	-0.0744	0.0581	0.0941	0.170
	(0.148)	(0.148)	(0.151)	(0.157)	(0.159)
Treated x Year of Disclosure	-0.0979	-0.0979	0.0723	0.0629	0.162
	(0.143)	(0.143)	(0.149)	(0.151)	(0.155)
Treated x 1 Year After Disclosure	-0.168	-0.168	0.0419	0.00660	0.131
	(0.156)	(0.156)	(0.167)	(0.166)	(0.172)
Treated x 2 Years After Disclosure	0.0327	0.0327	0.282	0.217	0.368*
	(0.191)	(0.191)	(0.203)	(0.201)	(0.208)
Treated x 3 Years After Disclosure	0.249	0.249	0.529**	0.464**	0.634***
	(0.197)	(0.197)	(0.214)	(0.212)	(0.221)
Treated x 4 Years After Disclosure	0.539**	0.539**	0.844***	0.748***	0.935***
	(0.211)	(0.211)	(0.230)	(0.230)	(0.240)
Treated x 5 Years After Disclosure	0.696***	0.696***	1.021***	0.900***	1.099***
	(0.240)	(0.240)	(0.262)	(0.273)	(0.285)
Age			0.239***		0.224***
			(0.0330)		(0.0322)
Age Squared			-0.00223***		-0.00214***
			(0.000509)		(0.000505)
1.treated	-0.119				
	(0.101)				
Constant	0.740***	0.657***	-0.404**	1.524***	0.289
	(0.0784)	(0.0580)	(0.200)	(0.198)	(0.257)
Inventor FE		X	X	X	X
Publication Year FE				X	X
Observations	19,008	19,008	19,008	19,008	19,008
R-squared	0.028	0.073	0.084	0.078	0.088
Number of Inventors	1,728	1,728	1,728	1,728	1,728

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

STRIKING THE BALANCE

Table 3: OLS Regression Results Excluding Spillover Control Observations

	(1)	(2)	(3)	(4)	(5)
4 Years Before Disclosure	0.219***	0.219***	0.190***	0.193***	0.154**
	(0.0594)	(0.0594)	(0.0603)	(0.0610)	(0.0618)
3 Years Before Disclosure	0.484***	0.484***	0.422***	0.458***	0.377***
	(0.0725)	(0.0725)	(0.0720)	(0.0797)	(0.0799)
2 Years Before Disclosure	0.725***	0.725***	0.627***	0.707***	0.581***
	(0.0861)	(0.0861)	(0.0867)	(0.0993)	(0.101)
1 Year Before Disclosure	0.978***	0.978***	0.839***	0.945***	0.771***
	(0.0923)	(0.0923)	(0.0919)	(0.113)	(0.115)
Year of Disclosure	1.487***	1.487***	1.306***	1.448***	1.224***
	(0.119)	(0.119)	(0.117)	(0.145)	(0.145)
1 Year After Disclosure	1.875***	1.875***	1.648***	1.822***	1.546***
	(0.114)	(0.114)	(0.116)	(0.154)	(0.157)
2 Years After Disclosure	1.889***	1.889***	1.614***	1.829***	1.499***
	(0.125)	(0.125)	(0.130)	(0.172)	(0.176)
3 Years After Disclosure	2.114***	2.114***	1.791***	2.057***	1.675***
	(0.129)	(0.129)	(0.142)	(0.189)	(0.199)
4 Years After Disclosure	2.029***	2.029***	1.659***	2.015***	1.581***
	(0.129)	(0.129)	(0.155)	(0.197)	(0.213)
5 Years After Disclosure	2.113***	2.113***	1.696***	2.116***	1.631***
	(0.134)	(0.134)	(0.174)	(0.203)	(0.231)
Treated x 4 Years Before Disclosure	0.0827	0.0827	0.0826	0.0790	0.0781
	(0.0857)	(0.0857)	(0.0857)	(0.0858)	(0.0858)
Treated x 3 Years Before Disclosure	0.0695	0.0695	0.0685	0.0726	0.0702
	(0.103)	(0.103)	(0.102)	(0.102)	(0.102)
Treated x 2 Years Before Disclosure	-0.00623	-0.00623	-0.00714	-0.0148	-0.0177
	(0.122)	(0.122)	(0.122)	(0.122)	(0.122)
Treated x 1 Year Before Disclosure	0.0258	0.0258	0.0255	0.0227	0.0201
	(0.138)	(0.138)	(0.138)	(0.137)	(0.136)
Treated x Year of Disclosure	-0.00756	-0.00756	-0.00807	-0.0116	-0.0150
	(0.161)	(0.161)	(0.161)	(0.160)	(0.160)
Treated x 1 Year After Disclosure	0.0897	0.0897	0.0888	0.0746	0.0704
	(0.168)	(0.168)	(0.168)	(0.167)	(0.167)
Treated x 2 Years After Disclosure	0.336*	0.336*	0.334*	0.330*	0.324*
	(0.184)	(0.184)	(0.184)	(0.183)	(0.183)
Treated x 3 Years After Disclosure	0.357*	0.357*	0.353*	0.345*	0.336*
	(0.198)	(0.198)	(0.199)	(0.197)	(0.198)
Treated x 4 Years After Disclosure	0.593***	0.593***	0.587***	0.572***	0.561***
	(0.205)	(0.205)	(0.205)	(0.204)	(0.205)
Treated x 5 Years After Disclosure	0.782***	0.782***	0.775***	0.754***	0.741***
	(0.228)	(0.228)	(0.228)	(0.227)	(0.227)
Age			0.0790***		0.0926***
			(0.0260)		(0.0271)
Age Squared			-0.000958**		-0.00104**
			(0.000409)		(0.000415)
1.treated	-0.184				
	(0.135)				
Constant	1.227***	1.156***	0.763***	1.090***	0.548*
	(0.0975)	(0.0558)	(0.216)	(0.230)	(0.325)
Inventor FE		X	X	X	X
Publication Year FE				X	X
Observations	23,430	23,430	23,430	23,430	23,430
R-squared	0.035	0.101	0.102	0.104	0.105
Number of Inventors	2,130	2,130	2,130	2,130	2,130

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1