

המכון למחקר כלכלי בישראל
על-שם מוריס פאלק בע"מ (חל"צ)
The Maurice Falk Institute for
Economic Research in Israel Ltd.



University Innovation and Local Economic Growth

by

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Discussion Paper No. 17.05

October 2017

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Naomi Hausman^{*}

Abstract

Universities, often at the center of innovative clusters, are believed to be important drivers of local economic growth. This paper identifies the extent to which U.S. universities stimulate nearby economic activity using the interaction of a national shock to the spread of innovation from universities – the Bayh-Dole Act of 1980 – with pre-determined variation both within a university in academic strengths and across universities in federal research funding. Using longitudinal establishment-level data from the Census, I find that long-run employment and wages around universities rise particularly rapidly after Bayh-Dole in industries more closely related to local university innovative strengths. The impact of university innovation increases with geographic proximity to the university and initial city size. Counties surrounding universities that received more pre-Bayh-Dole federal funding – particularly from the Department of Defense and the National Institutes of Health – experienced faster employment growth after the law. Entering establishments - in particular multi-unit firm expansions - over the period from 1977 to 1997 were especially important in generating long-run employment growth, while incumbent establishments experienced high turnover, consistent with creative destruction. R&D data from the Census indicate that large firms opening new establishments near universities in related industries after 1980 are indeed substantially more likely to have university R&D partnerships.

JEL Codes: R11, R12, O30

The Maurice Falk Institute for Economic Research in Israel Ltd.

Jerusalem, October 2017 • Discussion Paper No. 17.05

^{*} I am grateful to Ed Glaeser, Larry Katz, Josh Lerner, and Scott Stern for many helpful discussions. I also benefitted from conversations with Philippe Aghion, Pierre Azoulay, Jeff Clemens, Rebecca Diamond, Richard Freeman, Jeff Furman, Claudia Goldin, Joshua Gottlieb, Guido Imbens, Bill Kerr, and Josh Mitchel. I thank Crayton Scott Walker for assistance with geographical data. I acknowledge support from the Ewing Marion Kauffman Foundation, from the Center for American Political Studies at Harvard University, and from the Maurice Falk Institute at the Hebrew University of Jerusalem. Any opinions and conclusions expressed herein are those of the author and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. Correspondence: Naomi Hausman, Department of Economics, Hebrew University of Jerusalem, Mount Scopus, Jerusalem 91905, Israel. naomi.hausman@mail.huji.ac.il

1 Introduction

What is the effect of universities on neighboring industry? Many of the most innovative and entrepreneurial places in the United States cluster around research universities, such as Silicon Valley around Stanford and Boston's Route 128 corridor around Harvard Medical School and MIT. Such agglomeration of industrial activity may arise for a number of reasons, including shared inputs, local natural advantages, skilled labor pooling, and, importantly, knowledge spillovers (Marshall (1890), Krugman (1991)). The proximity provided by these clusters facilitates increased interaction and idea sharing between people, compounding the positive externalities of knowledge production and encouraging locally concentrated growth (Jacobs (1969); Lucas (1988)). Universities and research hospitals – important generators of new ideas and relatively disposed towards openness in discovery – are thus natural suspects as contributors to the local economy (Jaffe (1989); Furman and MacGarvie (2007); Kantor and Whalley (2009); Cantoni and Yuchtman (2014)). But feedback effects from business activity and common underlying factors affecting both universities and industry make universities' influence difficult to measure. This paper uses a new strategy based on universities' technological strengths and a change in federal policy to identify effects of universities on the growth of neighboring industry.

Before 1980, universities lacked strong incentives to commercialize research; the federal government held rights to all intellectual property produced by universities in the course of federally funded research.¹ But the December 1980 passage of the Bayh-Dole Act (Public Law 96-517), and its follow-on Trademark Clarification Act of October 1984 (Public Law 98-620), gave universities property rights to innovations developed under federal funding, and with these strong new incentives it opened a sea of patenting and licensing activity from universities as they developed infrastructure for technology transfer that they previously lacked (Henderson et al. (1998); Sampat et al. (2003); AUTM Licensing Activity Survey).² That this legal change fundamentally increased universities' connection to industry and induced greater spread of ideas from universities will help

¹Of course, some universities, especially public and land grant, were more practically oriented long before Bayh-Dole (Mowery et al. (2004); Sampat (2006); Goldin and Katz (2009)). Because they were so heavily funded by the states, they always faced incentives to be responsible to local industry. Even these institutions, however, tended to keep their commercial arms divorced from the university, administering patents through research foundations (like Wisconsin Alumni Research Foundation) or third parties such as the Research Corporation.

²New Congressional endorsement of the value of these activities to the economy may have also been important in changing the anti-commercialization sentiment harbored in many universities.

to identify their local effects.³

My strategy interacts the law change with cross-sectional variation in the extent to which industries are technologically related to nearby university innovation. Because universities produce more innovation – as measured by patents – in some technological areas than in others, I am able to identify the industries surrounding each university that are most likely to benefit from this increased spread of innovation after Bayh-Dole. The county-industry-specific innovation index I create provides variation both within university, between industries, and between universities due to their different industrial mixes. This type of variation has the advantage that I can hold a geographical location fixed and identify an effect off of cross-industry differences in the intensity of field-specific innovation from the nearby university. I am further able to address the concern that universities may simply innovate in the nation’s most quickly growing industries, such as biotech in the late 1980s and early 1990s, by controlling for nationwide changes in industry performance.

A natural additional test stems from the fact that, because Bayh-Dole affected federally funded inventions, universities receiving more federal funding before the law was passed were effectively more “treated” by the change: they had a larger affected research base from which the local economy could now benefit. I thus test whether areas grew differentially depending on the amount of federal research funding their local universities attracted in the several years before the Act was passed. I use detailed information on federal funding by agency and university to measure whether this effect holds for technological areas that might be especially closely tied to industry, such as those funded by the Department of Defense and the National Institutes of Health.

The Census Bureau’s Longitudinal Business Database (LBD) enables me to measure outcomes for detailed industries at a high level of geographic specificity from 1977 to 1997. The detail of the data permits tight connections between university strengths and related industry employment, payroll, wages, and establishment dynamics. Spanning twenty years, the data cover the passing of the Bayh-Dole Act and facilitate measurement of its immediate and longer-run effects. This long

³There is some dispute over the degree to which Bayh-Dole and its follow-on law altered research and commercialization practices in universities. Mowery and Ziedonis (2000) and Mowery et al. (2001) find in case studies of three universities that Bayh-Dole had little impact on the content of research but substantial impact on marketing efforts. Shane (2004b) finds that there was indeed a shift in university patenting after Bayh-Dole – whether or not the overall content of research changed – towards fields in which licensing is an effective mechanism of knowledge transfer. More comprehensive patent data indicate a substantial increase in university patenting after Bayh-Dole (Henderson et al. (1998); Sampat et al. (2003)), though this increase may reflect higher production of innovation, increased attention to commercialization of innovation, or both. By showing differential industry growth around universities after the law relative to before, my results shed light on the impact of the change brought by Bayh-Dole.

horizon provides a more comprehensive view of the substantial shift, marked by this policy change, in the relationship between research universities and their industrial neighbors.

I find that employment, payroll, and wages grow differentially faster after the Bayh-Dole Act in industries more closely related to the technological strengths of nearby universities. The magnitudes – 31 employees and \$1.5 million in payroll per county-industry after Bayh-Dole per standard deviation increase in the innovation index, or 13 employees and \$665 thousand in payroll per effective patent – are considerable and grow with geographic proximity to the university, supporting the importance of spatial relationships in the spread of knowledge. Areas surrounding universities that received more federal research funding before the law was passed grow faster after the law than do others; the effect is particularly large for DOD and NIH funding.

Isolating the effects of university innovation on local industry is a fundamentally difficult task because universities have developed together with their local economies over time, influencing each other and each being influenced by similar area fundamentals. University and industrial activity are thus naturally correlated: communications technologies, for example, developed in firms like Federal Telegraph in the nascent Silicon Valley just as they were developing in Stanford University laboratories. Use of a national external shock to this system, like Bayh-Dole, and in particular one whose theoretical impact differs across geographical and technological areas, brings new identification to this long-standing measurement problem.⁴ This strategy assumes that the industries and places I measure to grow the fastest after Bayh-Dole weren't already on faster growth trajectories, for reasons other than university research, before the law. Although the assumption of parallel pre-treatment growth trends cannot be tested in the LBD data because they do not stretch back far enough, aggregated data from County Business Patterns (CBP) suggest that such trends were not present.

Having shown significant employment and wage growth, I investigate whether the mechanisms behind this effect support the importance of both local knowledge spillovers and university-related

⁴Previous research has investigated the effects of university spending, as opposed to innovation, on growth. For example, Murray et al. (2016) use political instruments to identify the effects of state university spending on growth. Kantor and Whalley (2009) use changes in endowment spending to measure effects of university activity on local labor income. Other work by Adams (1990) measures how much productivity growth nationwide can be accounted for by stocks of knowledge stored in academic publications and finds lagged growth within scientific areas. Jaffe (1989) finds that corporate patenting in a state is related to local university research spending, controlling for industry R&D spending. Saha and Weinberg (2010) discuss, more generally, the challenges inherent in estimating the economic benefits of science and measure the relationship over time between local science spending and local wages.

entrepreneurship.⁵ An understanding of these mechanisms can inform both our models of agglomeration and our policy direction in encouraging local growth.

Entrepreneurs – whether thought of as entrants or as small firms – are often considered to be drivers of urban growth, and of innovation- and university-driven growth in particular (Glaeser et al. (2010, 2015); Agrawal et al. (2010); Shane (2004a)).⁶ Existing theoretical and empirical work suggests reasons why either entrepreneurs or existing powerhouses might be best-positioned to capitalize on university ideas. While entrants may be highly innovative and have been shown to add the most jobs from year-to-year employment growth economy-wide (Haltiwanger et al. (2013)), incumbents may have established relationships with universities, distribution channels, manufacturing expertise, and brand name that help to preserve their power. Small firms, and the inventors within them, may have the advantage of freedom to explore new and risky ideas (with potentially high payoffs) that large firms may avoid in favor of more immediate market rewards (Acemoglu (2009)). On the other hand, economies of scope and scale may help large firms take on new projects, having both the infrastructure to incorporate the work, the practical knowledge base to bring to new, related work, and the diversity to self-insure against the riskiness of a new project (Arrow (1962); Chandler (1990); Henderson and Cockburn (1996)).

I thus decompose the university growth effect to measure which types of establishments – entrants versus incumbents, large versus small – are most complementary with university innovation in producing employment growth. I find that while new activity in the university area and related industries is crucial, the entrant establishments that drive the growth effect do not satisfy our traditional image of entrepreneurs. Although large numbers of small, single unit firms enter university neighborhoods, supporting the idea that universities generated substantial quantities of spinoffs from their ideas after Bayh-Dole, these entrants are not the direct contributors to the bulk of the employment effect. Rather, existing multi-unit firms opening large new establishments nearby the university account for 65% of employment growth from entering establishments, and thus from universities overall. Meanwhile, incumbent establishments already operating in the vicinity of the university before 1980 experience higher turnover in industries most closely tied, technologically,

⁵See Agrawal (2001) for a review of some of the literature on the workings of university-industry knowledge transfer.

⁶We know much, descriptively, about differences in spinoff activity across institutions and industries (DiGregorio and Shane (2003)) but less about spinoffs' systematic contribution to growth.

with universities. This pattern suggests a creative destruction effect from university ideas and the firms that use them, consistent with recent theories of innovation and growth (Aghion et al. (2005, 2009)).

That multi-unit expansions to the geographic area around a university drive the employment growth effect is supported by evidence from the the confidential Business Research & Development and Innovation Survey (BRDIS) of the U.S. Census Bureau, which provides information on the kinds of idea sharing and innovation activities we would expect firms to engage in if indeed they are taking advantage of knowledge spillovers from the university. Linking the survey data to the LBD indicates that these large, multi-unit expansions after 1980 to the university area and related industries are exactly the ones most likely to engage in joint R&D activities with the university, to transfer IP, and to produce innovation of their own. With this evidence, one can thus trace the path of ideas from universities to industry growth.

The influence of universities is relevant for policy on multiple levels. National intellectual property policy, such as that contained in the Bayh-Dole Act, and federal research subsidies to universities both aim to enhance economic benefits derived from universities.⁷ Local policy makers in particular care about the benefits that accrue to university areas. Though many public attempts to generate clusters of innovation and entrepreneurship fail at huge cost (Lerner (2009)), the importance of certain local factors, like skilled populations, is generally accepted (Glaeser et al. (1995); Moretti (2004)).⁸ Other evidence stresses the positive agglomeration spillovers from entry of large plants (Greenstone et al. (2010)). My results emphasize the importance of universities – and the large firms they attract – for local growth.⁹

⁷Because ideas are a non-rival good that can generate increasing returns to scale, they may be privately under-produced and warrant public subsidies and/or intellectual property protection to increase the expected return to investing in discovery (Romer (1986); Jones and Romer (2010)). The U.S. government engages in both of these means of encouraging research.

⁸Efforts to stimulate neighborhoods within cities via state Enterprise Zones or federal Empowerment Zones have met with mixed results (Neumark and Kolko (2010), Busso et al. (2013)).

⁹Creating a strong university from nothing is obviously a difficult task. Using universities as a policy tool is more common in the context of marginal research subsidies, intellectual property law, or efforts to encourage university-related entrepreneurship, though new universities are still being founded around the world today, some specifically with local development objectives.

Whether a policy to stimulate a local economy via its university would be welfare-enhancing nationally is a separate question (Glaeser and Gottlieb (2008)). Place-making policies require more justification than just evidence of stimulative local effects. In particular, they require non-linearities in agglomeration economies: benefits of one place growing outweighing losses from another shrinking. In the case of universities and local industry growth, it may well be that firms shift operations away from other geographical areas to be close to and benefit from universities. I do not address net effects of universities on industry growth across geographic areas.

The remainder of the paper is structured as follows. Section 2 provides background on the Bayh-Dole Act, its effect on the incentives universities face, and how it generates a useful setting in which to study the economic effects of university innovation. Section 3 proceeds to develop the empirical strategy, while section 4 describes the multiple data sources used in measurement. Section 5 presents the main results of the paper and section 6 discusses associated endogeneity concerns. Section 7 investigates the mechanisms through which universities stimulate growth by measuring the roles of different types of establishments, and section 8 concludes.

2 Innovation Policy and The Bayh-Dole Act

Historically, and through the 1960s and 70s, many American universities shied away from direct involvement in commercialization of research. Though some justified it from the perspective that patenting and licensing took knowledge out of the public domain, their avoidance was substantively rooted in a fear of political embarrassment. Patenting could compromise the university's commitment to open science, they thought, and the profit motive inherent in licensing could undermine the purity of the scientific endeavor. At Columbia University, for example, administrators felt "it is not deemed within the sphere of the University's scholarly objectives" to hold patents (Sampat (2006)). And until the 1970s, many top universities, including Harvard, Yale, Johns Hopkins, Columbia, and the University of Chicago explicitly forbade the patenting of biomedical research.

Neither was the legal regime before the Bayh-Dole Act of 1980 supportive of commercialization. The federal government held rights to intellectual property developed in universities under federally funded research, which was a large component of total research conducted: in each year from 1972 to 1980, 66-69% of university research expenditures were from federal sources.¹⁰ Researchers could patent their innovations if they wished, but with government presumption of title, they could not keep royalties from licensing unless they negotiated a special Institutional Patent Agreement (IPA) with the granting agency. Policies regarding these agreements varied widely across agencies; as a result, any attempt on the part of a researcher to secure patent ownership and royalty rights tended to involve lawyers, negotiations, drafts of agreements, and other administrative red tape. Mean-

¹⁰These percentages represent averages across all universities and colleges surveyed; some institutions may have even higher federal funding shares. The statistics were calculated from data in the NSF Survey of Research and Development Expenditures at Universities and Colleges.

while, though government title suggests a regime of “open science,” in practice most innovations in the public domain effectively sat in a drawer, not heavily publicized or commercialized: only 5% of the 28,000 patents owned by the federal government in 1976 were licensed.¹¹

Certainly there were some universities involved in patenting on a smaller scale before Bayh-Dole, but even so, they kept their commercialization activities at arm’s length to avoid its direct association with the university.¹² Many of these were public and land grant universities that had always been more practically oriented and responsible to their local economies (Goldin and Katz (2009)).

Debate leading up to the law focused largely on the economic issues involved: the positive externalities of public knowledge versus private incentives to innovate.¹³ The World War II expansion of defense R&D put substantially more money in the hands of universities and corporations and raised the stakes on patent law. The government felt that federally financed innovations should be kept in the public domain to maximize potential spillovers (although of course it could have been at least somewhat motivated by a desire to return to government coffers some of the profits from government funded innovation). Others worried that companies would not fully invest in discovery without stronger intellectual property protection allowing them to benefit from innovation developed in the course of contract R&D. Rising uncertainty over U.S. economic competitiveness heightened the pressure to produce innovation at the highest level, unhindered by burdensome legal code.¹⁴

In December 1980, Congress passed the Bayh-Dole Act, which standardized patent policy across granting agencies and reversed the presumption of title to inventions developed under federally funded research. Whereas before, rights to any government funded innovations developed in uni-

¹¹Federal Committee on Science and Technology (FCST) Report, 1976.

¹²There were two prominent means by which universities patented in this period. The first was to contract with the Research Corporation, an independent institution which administered patents of a number of universities. The second was to establish a research foundation only loosely affiliated with the university, a good example of which is the Wisconsin Alumni Research Foundation (WARF), which had already administered a significant number of patents before Bayh-Dole.

¹³The nature of this debate might lead one to think that Bayh-Dole would provide a natural setting in which to test the economic effects of IP protection relative to open science, in the spirit of Murray and Stern (2007), Aghion et al. (2009), and Williams (2013). However, because the Federal government did not actively publicize the IP to which it had rights before Bayh-Dole, and commercialized only a small portion of it, the pre-1980 IP regime is likely not appropriately representative of “open science,” leaving no useful counterfactual for such a test of IP rights, per se.

¹⁴University lobbyists were also involved in the debate but were by no means the focus. Much of the debate was centered on contracting firms, as discussed above, and witnesses from both universities and small businesses appeared in the hearings.

versities accrued to the government, now universities could patent, own rights to, and keep royalty revenues from these innovations. The rights came with a responsibility to actively promote the inventions' commercialization and satisfy a number of other simple criteria, including granting the federal government a non-exclusive license and sharing any royalties with the inventor. Further strengthening the rights of universities, Congress passed the Trademark Clarification Act in 1984, which removed some restrictions on the types of inventions universities could own and on the transfer of property rights to other parties. Together, these laws significantly strengthened the incentives of universities and faculty to produce, patent, and commercialize innovation.¹⁵

Universities and faculty responded to these new incentives.¹⁶ Though some universities housed technology transfer offices (TTOs) to administer patents before Bayh-Dole, others opened these units at much higher rates in the mid 1980s and through the early 1990s (Figure 1). Patenting from universities rose correspondingly (Henderson et al. (1998)), with the sharpest increase beginning in the late 1980s as university infrastructure adjusted to handle faculty disclosures, patent applications, and licensing on a large scale (Figure 2). While only 55 universities had been granted a patent in 1976, 340 universities had been granted at least one patent by 2006.¹⁷ Although it is difficult to say whether faculty responded by producing more innovation after Bayh-Dole, since it's possible that existing innovation simply wasn't patented at high rates beforehand, there is evidence from the 1990s that faculty respond to stronger royalty incentives by producing higher quality innovation (Lach and Schankerman (2008))¹⁸. The increasingly commercial orientation of universities indicated by higher patenting and more TTO openings was likely also borne out in closer connection of academics to industry more generally via consulting relationships, start-ups,

¹⁵In most of the paper, I refer loosely to the Bayh-Dole Act as the law change being used for variation, but in fact, these two laws together comprised the change in the legal regime. Most of my analysis considers December 1980 to be the beginning of the change and, accordingly, 1982 to be the first Economic Census data year after the change began.

¹⁶It may be that the incentives created by Bayh-Dole induced faculty to shift focus from basic to more applied research. I do not directly measure this possible behavioral change; one would need, at a minimum, measures of basic and applied research output from universities before and after the law, perhaps in the form of publications classified according to these categories. Moreover, it's not clear what one would infer from a result that there was a shift in research topics, as it's difficult to know what balance of basic versus applied research is socially optimal. Thursby and Kemp (2002) and Thursby and Thursby (2007) discuss these issues; Lazear (1997) and Thursby and Thursby (2007) develop models clarifying possible behavioral effects generated by licensing and funding incentives. Azoulay et al. (2007) find that, among life scientists, patents tend to go along with a flurry of academic publications, suggesting that even if research does become more applied, it's still basic enough to be within the realm of the academic.

¹⁷Counts were calculated from NBER patent data.

¹⁸There is also suggestive evidence that patenting increased most after Bayh-Dole in lines of business which most value technology transfer via patenting and licensing (Shane (2004b)).

and so on. I provide evidence suggestive of these increased connections in section 7.2.

Thus in terms of both underlying culture and explicit incentives, the Bayh-Dole Act marked a great shift in the relationship between universities and industry. With congressional endorsement banishing much of the remaining hesitation to engage in patenting and licensing, these activities ceased to be political embarrassments and instead became testaments to a university's prestige. The sort of large scale technology transfer and, more generally, idea transfer from universities that exists today would have been very difficult and likely impossible to achieve without the strengthened property rights, standardized across granting agencies, that were set into law in 1980 and 1984.

3 Universities in the Local Economy

One of the key arguments – and tested predictions – in this paper is that universities are likely to have disproportionately local growth effects because of local knowledge flows. This section discusses several possible mechanisms through which universities may stimulate their local economies in particular.

Economists have long considered knowledge flows to be facilitated by face-to-face interactions between people. In 1890, Alfred Marshall wrote that in industrial clusters, “the mysteries of the trade become no mysteries; but are as it were, in the air,” reflecting the notion that important knowledge is often transmitted without being written down. Lucas (1988) agreed that “most of what we know we learn from other people” and argued that oral transmission of knowledge is an important part of why people cluster together in cities despite the increased costs – as in the form of higher land prices, for example – that such clustering imposes. Substantial theoretical and empirical evidence supports the notion that innovation and entrepreneurship come in large part from the mixing of ideas in localities (Glaeser et al. (1992); Duranton and Puga (2001); Agrawal et al. (2008)), and that use of innovation is disproportionately local (Jaffe et al. (1993); Kerr (2010)).¹⁹ Universities are likely to be focal points of such idea flows, given evidence of their high production of ideas, their connectedness to nearby industrial activity (Jaffe (1989); Furman and MacGarvie (2007); Kantor and Whalley (2009); Cantoni and Yuchtman (2014)), and their attraction of patent citations disproportionately from local areas (Belenzon and Schankerman (2010)).

¹⁹For more discussion and evidence of local knowledge flows, innovation, and entrepreneurship, see Marshall (1890); Chinitz (1961); Jacobs (1969); Saxenian (1994); Fallick et al. (2006); Simonen and McCann (2008).

Ideas produced in universities may stimulate industry growth through a variety of mechanisms. Some ideas are codified in the form of patents or publications, and workers in industry may access them via license or purchase. Other ideas are transmitted in person or are even embodied by and inseparable from individuals with tacit knowledge, or know-how. Industry may benefit from these ideas by hiring university students or faculty either full time or as consultants, or the academics themselves may start private ventures (start-ups). Evidence on some of these mechanisms already exists. Skilled workers, trained in or attracted to an area, have been shown to predict subsequent area income growth (Glaeser et al. (1995)); in particular, the presence of land grant universities generates growth via increased area skills (Moretti (2004)).²⁰ Universities may also generate local amenities – for example, musical or artistic performances – that would attract people to the area.²¹ In section 7.2, I provide evidence of a growth mechanism that works more clearly through knowledge transfer to firms rather than through skills per se: companies that locate nearby universities after Bayh-Dole and do business in related technologies are substantially more likely to engage in relationships with universities that facilitate knowledge transfer.

Of the large number of channels through which university ideas can diffuse to industry, a few - such as publications and conferences - do well at spreading information over great distance, while many - hiring, consulting, patenting, and spinoffs, for example - can and do have a local bias. Though patents contain knowledge that is in principle easy to access from afar, they may have complementarities with non-codified ideas or know-how that would lead to a differentially high local return to codification (Arora (1996)). These complementarities are important to consider in the context of the Bayh-Dole Act, which increased incentives for universities to codify knowledge in the form of patents. If patents are complementary with in-person knowledge sharing, then one might expect differentially high local relative to global economic growth effects after the law.²² Alternatively, if codified and non-codified knowledge are substitutes, then high patenting from

²⁰Skilled human capital also predicts higher service firm formation rates (Acs and Armington (2004)).

²¹To the extent that these multiple modes of university influence are correlated with my measure of universities' technological strengths or are complementary with university innovation, they may be captured in my estimation to comprise a more general "university effect." Complementarities in local growth between technology and investment in skills from higher education has been suggested before (Aghion et al. (2009)).

²²Jensen and Thursby (2001) provide theoretical grounds for complementarities of patents with in-person interactions. Hellmann (2007) explores a theoretical mechanism that may or may not result in net complementarities of patents with university-firm relationships. Belenzon and Schankerman (2009) document that some universities incur costs to promote local development objectives via local technology transfer. Gaspar and Glaeser (1998) examine the theoretical and empirical effects on cities of electronic communication, which, like codified knowledge, may complement or substitute for face-to-face interaction.

universities following Bayh-Dole would be expected to have diffuse growth effects.

There is reason to believe that these complementarities between codified knowledge and face-to-face interactions exist and can be important in the context of universities. Evidence suggests that firm success is related to the local prevalence of top scientists in related technologies, likely because of their hands-on involvement (Zucker and Darby (2007)). Further effort on the part of the scientist can be necessary to develop a licensed invention into a commercializable product given the embryonic phase at which many inventions are legally transferred (Jensen and Thursby (2001); Thursby and Thursby (2007)). And co-mingling patterns of university and industry scientists in some fields further suggests that much learning occurs in person even upon transfer of a codified technology (Murray (2002); Cockburn and Henderson (1998)). Much university knowledge, even the type that can be written down, seems to be better-accessed with an in-person component.

To understand local industry effects of universities, one would ideally like to randomly allocate universities to locations and measure related industry activity in those locations after the universities arrived relative to before. Treating only one of two similar areas with a university would generate clearly defined treatment and control groups for comparison under the hypothesis that local effects will be differentially larger than global effects. Of course, in reality universities exist non-randomly in their locations, and areas with universities differ from those without.

To approximate the ideal experiment as well as possible in the real world, I use a shock to the spread of ideas from universities, combined with cross-sectional variation between universities in the way in which they are likely to affect their surroundings after the shock. Further, these cross-sectional differences provide variation even within-area and between affected industries such that changes in area-level economic performance can be held constant.

More concretely, I argue that the Bayh-Dole Act serves as the change after which universities relate to industry in a fundamentally different way, more eager to commercialize their research. Because universities have a different mix of research strengths, they produce innovations that feed into a different mix of industries. For example, the University of Texas at Austin, which has top electrical and computer engineering departments, is likely to stimulate local engineering industries more than local pharmaceuticals, while Johns Hopkins University, which specializes in biomedical sciences, will do the reverse for Baltimore. As such, we are likely to see differences in growth between industries within each of these geographical areas.

In a measure called an “innovation index,” I capture the extent to which a university’s innovation is likely to stimulate each industry around it. The technology classes of the patents produced by each university, combined with a patent-industry concordance, allow me to calculate an innovation index for each 3-digit SIC industry in the area around each university.²³ I measure outcomes such as employment, payroll, and average wages in each industry in each county. It is important to note that patents are used here as a measure of the universities’ technological strengths and as a means to connect university ideas to the industries that are likely to benefit from them; the measure does *not* imply that the only mechanism through which universities can affect industry in my estimation is via patenting and licensing of innovation. Rather, because of universities’ generally increased connection to industry after the Bayh-Dole Act, they are likely to have an increased effect on industry via any of the mechanisms described above.

Formally, this strategy amounts to estimating an equation in which an outcome y in county c , industry i , and year t is regressed on the innovation index measure, $index_{ci}$, and the interaction with an indicator, $I\{aBD\}_{ct}$, equal to 1 after the Bayh-Dole Act in counties near universities:²⁴

$$(1) \quad y_{cit} = \beta_0 + \beta_1(index_{ci}) + \beta_2(I\{aBD\}_{ct} * index_{ci}) + \phi_{it} + \psi_{ct} + \epsilon_{cit}$$

The coefficient β_2 on the interaction term measures the differential effect of universities on high index relative to low index industries in a given county after the passage of the law relative to before. It is expected to be positive for employment and payroll outcomes if university innovation has stimulative effects on related industries. The effects on average wages, calculated as payroll per worker, are a bit more difficult to think about theoretically because, without a measure of hours worked, it does not literally represent labor productivity. However, average wages are highly correlated with value added per worker during my sample period in the U.S.: the correlation between the two in the Annual Survey of Manufacturers at the 4-digit SIC level from 1977 to 1997 is 0.66.²⁵ To the extent that average wage reflects labor productivity, one might expect β_2 in that regression to be positive if university innovation generates not only more work but also

²³I describe the construction of the innovation index in more detail in the data section of the paper.

²⁴Note that the main effect of $I\{aBD\}_{ct}$ is excluded because it is perfectly colinear with the county-year fixed effects, ψ_{ct} .

²⁵This correlation is calculated using the 1987 SIC version of the NBER-DES Manufacturing Industry Database, 1958-2005, publicly available for download at <http://www.nber.org/data/nbprod2005.html>.

more productive work in an industry. Without a more detailed model, however, there is no clear prediction for this outcome. One could imagine a decline in average labor productivity if the composition of workers needed in an industry has changed, though it seems more likely that the new technologies would be complementary with highly skilled workers (Autor et al. (2003)).

In practice, because I include in the regressions all counties in the nation, $I\{aBD\}_{ct}$ equals 1 after the law only for counties containing or nearby one of the innovating universities in my sample.²⁶ Similarly, industries in counties not near a university are not treated with a positive innovation index. In my main specifications I include county-year fixed effects, ψ_{ct} , to control for location-specific factors that vary by year; this effect picks up any cross-industry changes over time in each location. My preferred specifications also include industry-by-year fixed effects, ϕ_{it} , to control for nationwide industry-specific factors in a given year.²⁷

In addition to using cross-sectional variation in the innovation index to measure the effect of universities, I employ variation across universities in the amount of federal funding they received for research in the years before Bayh-Dole. Because the law affected patent rights specifically for inventions developed in the course of federally funded research, universities that had more funding would have had more research affected by the law. This test uses variation across geographical areas and within geographical areas over time, but not within a geographic area in each year, as does the previous analysis. It is useful in that it connects industry outcomes to government inputs, both overall and for specific grant-making agencies.²⁸

The estimated regression has a similar structure:

$$(2) \quad y_{cit} = \alpha_0 + \alpha_1(\text{fund}_c * I\{aBD\}_{ct}) + \phi_{it} + \delta_c + \nu_{cit}$$

where outcome y in county c , industry i , and year t are the same as those above, fund_c is the sum of federal research funding received by the nearby university in 1976 – 1980, the five years leading up to Bayh-Dole, and $I\{aBD\}_{ct}$ is, as before, an indicator equalling 1 after the law for counties

²⁶Counties not in proximity to a university are included in the regressions because they help to estimate the industry-by-year fixed effects.

²⁷Note that county-industry fixed effects cannot be included because they would be perfectly colinear with the innovation index, which varies at the county-industry level but not over time; the main effect of the innovation index is included.

²⁸Freeman et al. (2010) discuss at greater length the estimation of returns to R&D spending.

near universities.^{29,30} ϕ_{it} are industry-by-year fixed effects to control for nationwide changes in industry-specific performance, and δ_c are county fixed effects, such that the regression compares the growth of better-funded counties with the growth of less-funded counties. α_1 is expected to be positive if federal funding translates into industry growth via research.³¹

Finally, though the geographic nature of this exercise has been implicit throughout the description, I also explicitly use geography for identification of spatial differences in effects. In my main specifications, “university counties,” or those near universities, are all counties within 75 miles of the university. To zero in on the effects of proximity, I re-estimate my main regressions allowing universities to treat only the counties that contain them. An increase in the coefficient of interest when the influence of a university is narrowed suggests a larger effect on industry that is more proximate to and thus more able to interact with the university.

4 Data

This paper uses several data sets from distinct sources, each of which I briefly describe here.

4.1 The Longitudinal Business Database (LBD)

The Longitudinal Business Database (LBD) of the Census provides the outcome data I use in my analysis.³² It covers all U.S. private non-farm business establishments that file payroll taxes with the IRS from 1976 to 2005; these are establishments with at least one paid employee. For each establishment, there is information on employment as of March 12 of that year and annual payroll, as well as year of entry, year of exit, and detailed industry classification.³³ My analyses are run at the county-industry-year level, though I use the longitudinal aspect of the data to build up from the

²⁹Note that the main effect of federal funding, $fund_c$ is excluded because it is colinear with the county fixed effects.

³⁰If there are multiple nearby universities, the funding for all of them is summed.

³¹Note that with this specification I can’t rule out the possibilities that 1) federal funding is capturing other attributes of universities that lead to growth, and/or 2) federal funding goes disproportionately to areas of the country that are growing quickly after Bayh-Dole for reasons other than the nearby university.

³²More detail on the construction of the LBD can be found in Jarmin and Miranda (2002).

³³Though the publicly available County Business Patterns (CBP) data set contains employment and payroll information by industry at the county level, which is the level at which I ultimately run my regressions, it lacks several crucial characteristics of the LBD. First, it censors information in small county-industry groups, a shortcoming that becomes more serious in early data years such as those before my policy change. In 1977, 1982, and 1987, approximately 70% of the CBP data is censored. Second, it does not allow tracking of establishments over time, precluding deeper analysis of the composition of changes that occur. Finally, there are design differences in the two datasets - in part due to corrections made using longitudinal information - that cause them to diverge.

micro level. I aggregate establishments within a county to their 3-digit SIC classification to match to patent technology classes, and I cut off my analysis in 1997, before the switch to NAICS codes is made.³⁴ The long time span of my data and the increased reliability of LBD data in economic census years – those ending in 2 or 7 – lead me to employ data from the five census years between 1977 and 1997 in my main set of results.

4.2 NBER Patent Data

The National Bureau of Economic Research Patent Data Project provides a compiled version of publicly available data from the United States Patent and Trademark Office (USPTO) on utility patents granted between 1976 and 2006 (Hall et al. (2001)).³⁵ The data contain year of patent application and grant, assignee, and the patent technology class, among other things. Assignees (patent owners) may be individuals, U.S. or foreign corporations, U.S. or foreign governments, hospitals, or universities. I use the subset of patents assigned to universities and university-affiliated hospitals to select my sample of innovating universities and to connect the research fields in which each university is highly innovative to the industries that may use a university’s innovations.³⁶

As previously described, university patenting grew substantially over time, from 294 patents granted in 1976 to 2,369 granted in 1997 (Figure 2). Patenting also became more pervasive; in 1976 only 55 universities were granted patents, but 269 universities had been granted at least one patent by 1997 and 340 by 2006.

The patent data are an important part of the estimation strategy because they measure each university’s technological strengths and thus provide the link between university research and the nearby industries which are likely to experience growth. The next section describes in detail how the county and industry-specific measure of innovation is constructed.

³⁴There exist many-to-many concordances between SIC and NAICS industry classifications, but because my analysis is long-term in nature and spans 20 years as is, marginal “after” years are unlikely to justify the noise that would be added by attempting to translate industry codes.

³⁵The NBER patent data have been updated since the version discussed in Hall et al. (2001), which only contained patents granted through 1999. The updated data can be downloaded from the NBER patent data project website: <https://sites.google.com/site/patentdatapoint/Home>.

³⁶The sample I select includes all universities that produced at least 7 utility patents and all hospitals that produced at least 4 utility patents granted between 1976 and 2006, the entire period of the data. Patenting is highly concentrated among the top universities and hospitals, so for each group a cutoff was imposed where the tail of the distribution thinned significantly. For both universities and hospitals, the institutions selected produced more than 95% of patents from their institution type in this period.

4.2.1 Constructing the Innovation Index

To construct the measure of university innovation, I begin with patents produced by universities and hospitals in my sample through 1985 – the first year after the October 1984 passage of the Trademark Clarification Act.³⁷ Each patent of each university is assigned a technology class by the USPTO. On their own, these technology classes are difficult for a non-specialist to interpret in terms of their significance to various industries. However, following Kerr (2008), I use a probabilistic concordance, constructed by experienced practitioners, that weights each 3-digit SIC industry (SIC-3) in terms of the probability it will use a patent with a given technology classification.³⁸ The weights sum to one across SIC-3 industries for each USPTO technology class. The university-industry-specific index is thus a sum of the weights across a university’s patents and within an SIC-3 industry. For counties that experience effects of multiple universities, this index then has to be summed across universities. The final measure is constructed according to Equation 3, where p is the number of patents granted to university u in technology class n , and w is the frequency of use weight for patent class n in industry i .

$$(3) \quad index_{ci} = \sum_{u \in c} \sum_n w_{in} * p_{un}$$

Figure 3 presents a simple example of how to construct a university’s innovation index from a concordance. Each university ends up with an innovation index for each of approximately 400 SIC-3 industries, and the university weights are summed across universities in a county as shown in Equation 3. The measure incorporates both the relative intensity (across technology classes) and the scale (number of patents) with which the university innovates in a field.

The resulting innovation index measure indeed captures the cross-industry differences in use of university innovation that one might think it should. Examples of high index industries in

³⁷Ideally, one might want to create a measure of the innovation index based only on the pre Bayh-Dole innovation of universities, although the legal regime was not totally changed until the follow-on law was passed near the end of 1984. The goal would be to exclude possible feedback effects of industry into the research agenda. Because patenting from universities was much less common before Bayh-Dole than afterwards, using only early patents is likely to miss much of the research activity that existed. However, given plausible research lags, patents granted in 1985 would have been produced almost entirely by research initiated before Bayh-Dole, and certainly before the Trademark Clarification Act. The advantage of using patents until 1985 is precision in measuring the innovation index for each university.

³⁸This concordance updates work done by Brian Silverman and dates back to a period in the early 1990s when the Canadian patent office assigned multiple classifications to each patent upon granting. They assigned not only the technology class of the patent, but also its industry of use. Thus for each technology class there would be a distribution of industries of use from which this probabilistic concordance could be derived.

the sample include: medical equipment (including surgical, electrotherapeutic, and x-ray); photographic equipment and ophthalmic goods; machinery and tools; computers, storage, and associated equipment; communications, electronics, and semiconductors; chemicals, pesticides, pharmaceutical preparations, and diagnostic substances; national security, aircraft, guided missile/ space vehicle parts and propulsion; small arms and ammunition; search, detection, and navigation systems and instruments. Biomedical industries are especially prevalent among high index industries. Low index industries include, for example: finance, accounting, banking, insurance, brokers; clothing retail (and some production, e.g. leather gloves and mittens); transportation and carrying services (e.g. taxi, bus, freight, USPS); administration of educational, public health, and social programs; dealers: motor vehicle, RV, boat, motorcycle; construction materials: brick, stone, sand and gravel, crushed granite.

Most of these low index industries are generally low-skill and probably do not use much innovation produced by universities. The one notable exception is finance. In fact, there are a number of important financial innovations that emerge from universities and are used regularly by practitioners; take as a famous example the Black-Scholes option pricing model, which was developed in academia and for which the 1997 Nobel Prize in Economics was awarded to Robert Merton and Myron Scholes. However, because financial innovations are not generally patentable, this measure of university innovation will tend not to pick up innovations used by these industries, and they will score low on the innovation index.

Finally, note that the resulting measure of the index is highly skewed, as expected given 1) the high concentration of patenting among a few top universities and 2) the greater prevalence of patenting in some fields over others. The standardized version of this variable, mean zero and standard deviation 1, remains skewed; it is summarized in Table 1.

4.3 NSF Federal Research Funding to Universities

Data on federal research funding to universities from 1963 to 2007 come from the National Science Foundation's publicly available survey on *Federal Science and Engineering Support to Universities, Colleges, and Non-Profit Institutions*. The data contain amounts of funding by government agency, university campus, category of spending, and year. There are approximately 100

agencies and 25 departments to which they belong.³⁹ Having the data on the university campus level, as opposed to the university level, is important for a system like the University of California that has multiple innovating campuses spread widely around the state.

In addition to providing funding amounts, these data also provide geographical locations for each campus – city, state, and zip – which allow me to assign each of them latitude and longitude coordinates (to define their local areas) as well as to assign them to counties using geocoding software.

To give a sense of the funding magnitudes, in 1980, MIT was receiving \$163.2m in total funds, \$26.9m of which came from the DOD and \$27.2m of which came from NIH. A much less research-intensive university, Montana State University at Bozeman, was also receiving significant federal funds in 1980: \$10.6m total, \$381k DOD, and \$346k NIH. Like patents, federal funding is also highly concentrated among top universities: the top five university campuses out of over 200 in my sample attracted nearly 20% of that group’s federal funding dollars between 1976 and 1980.

4.4 Geographical Data

My empirical analysis relies on knowing not only where universities and hospitals are, but also on knowing which counties are nearby. I use Geographic Information Systems (GIS) software to translate geographical information I have on these institutions into information that is compatible with the organization of the LBD. In particular, the software can produce approximate latitude/longitude coordinates and a county code containing each {city,state,zip} triplet. It can also produce the codes of all adjacent counties and, further, can list all counties within a specified distance.

In most of my analysis, I consider all counties having any part within a 75 mile radius of an innovating university to be “university counties.” All university counties are considered to be treated both by my “innovation index” measure of innovation and by federal funding from the nearby universities. The radius of 75 miles was selected with the goal of being inclusive in any part of the U.S. In other words, though this distance seems large for the compact places of the northeast, it can be moderate for places in the south and west. Rather than adjusting the circle size around universities by region, I use a uniform circle size nationwide and perform tests in which

³⁹Data are reported only on the level of the department until 1971.

I adjust circle size for all parts of the country simultaneously.

4.5 Main Sample

The sample that results from combining these various data sources contains observations at the county-industry-year level, where industries are 3-digit SICs and included years are the five census years during the period: 1977, 1982, 1987, 1992, and 1997. Because there are often multiple universities and hospitals in a given county or in nearby counties, each of their associated “treatment effects” – federal funding and the innovation index measure of innovation – are summed within treated county-industries. Thus the set of counties around Harvard, Harvard hospitals, and MIT are treated by the sum of federal funding to all three institutions. Within each surrounding county, a biomedical industry, for example, would be treated by the biomedical innovation index that is the sum of those from each of those schools. The resulting data set contains one observation for each county-industry-year, even if that unit is treated by more than one institution. Bayh-Dole treats only university counties – counties containing or surrounding a university or research hospital – in the years after 1980. Table 1 presents descriptive statistics on the main sample.^{40,41}

5 Main Growth Results

5.1 Related Industry Employment Growth

Table 2 presents the main employment results. Column 1 regresses employment on the standardized measure of the innovation index and on the interaction of the innovation index with an indicator equalling 1 after Bayh-Dole, with county-year fixed effects that absorb the main effect of the law change. The coefficient on the interaction term indicates an increase of approximately 39 workers per county-industry after Bayh-Dole for a standard deviation increase in the innovation

⁴⁰Note that mins and maxes have been rounded to satisfy Census Bureau confidentiality requirements, and that medians are not releasable.

⁴¹Note that these statistics reflect a sample with a large number of zeros for county-industry-year outcomes. There are two reasons why a county-industry-year may have zero employment and payroll but still be in the data. First, some industries appear in a county in some years but not in others, usually entering at some point in the 20 year period I study and then remaining. That some industries enter in certain counties and others don’t, however, does not imply that no other industries could have entered. In fact, all industries that are treated by university innovation have some latent propensity to enter and we only observe the ones that cross some threshold and enter. Ignoring industries that are treated but don’t enter would miss part of the treatment effect (Seim (2006)). Inclusion of these county-industries is the second reason for zeros in the data. All treated industries in university counties are included in the sample. The panel is thus also balanced.

index. Because this specification includes county-by-year fixed effects, the estimate tells us that industries more closely related to the local university’s innovation experienced substantially greater employment growth after Bayh-Dole than did less related industries in the same county, controlling for overall county size in a given year. Column 2 adds industry-by-year fixed effects to control for national industry-specific changes. Thus the coefficient of 30.51, slightly diminished from column 1, accounts for the fact that university-related industries may be nationally the most quickly growing ones, and it measures only the additional employment growth due to nearby university innovation.⁴²

5.2 Growth in Average Establishment Size

Columns 3 and 4 show an increase in average establishment size for treated industries within a 75 mile radius; the magnitude with industry-by-year fixed effects is nearly 2 workers per establishment per year for a standard deviation increase in the innovation index. This result is a first suggestion that there may be something about university innovation that is complementary with large establishments.

5.3 Growth in Labor Productivity

Table 3 shows analogous results for payroll and wage outcomes. A standard deviation increase in the innovation index generates an additional \$1.83 million in payroll per county-industry after Bayh-Dole (column 1), and a \$222 increase in wages per standard deviation increase in the innovation index (column 3). Though the wage effect is not significant when industry-by-year effects are added and coefficients are averaged across the four census years following Bayh-Dole (1982, 1987, 1992, 1997), it is significant by 1997 even with the additional fixed effects (Table 4, column 6). Per standard deviation increase in the innovation index, the 20 year effect on wages is \$342 with county-year fixed effects and \$208 with industry-by-year fixed effects added. To the extent we believe average wages reflect labor productivity, this result suggests an increase in average labor productivity in industries that more heavily use university innovation.⁴³ In other words, universities

⁴²In particular, the existence of a strong effect in this specification rules out the possibility that the university effect I measure is driven by the coincident boom in biomedical industries to the extent that it was a general trend and not specifically related to universities.

⁴³Average wage, measured by payroll per worker, does not directly measure labor productivity because it does not account for hours worked. However, average wage is correlated 0.66 with value added per worker at the SIC4 level

are generating not just more work, but also likely more productive work.

5.4 Timing of Effects

For both employment and payroll outcomes, effect sizes seem to rise over time after Bayh-Dole and flatten out by 1992 and 1997 (Table 4 and Figure 4), further supporting the notion that the brunt of the change occurred directly in the wake of Bayh-Dole. The continued adjustment to a steady state makes sense, though, given the gradual pace with which universities altered their infrastructures and attitudes to the new commercialization regime after the Act. They opened technology transfer offices at low rates in the early 1980s and at very high rates in the late 80s and early 90s (Figure 2). Without these offices, most researchers would not be bothered to initiate a long and elaborate process of patenting and licensing a discovery. But with these offices in place, patenting from universities shot up in the late 80s and early 90s. The gradual opening of these TTOs reflects the more generally gradual opening of researchers and universities to engagement with industry in various ways, including through consulting, startups, and so on. And the increase in employment growth in related industries at that time mirrors this growing connectedness of universities to industry.

5.5 Magnitudes

The total 20 year effect of university innovation on employment growth is large when compared with the base employment of 100 workers per county-industry, on average, in university counties. Taking the 1997 estimate from column 2 of Table 4, the increase of 34 workers per standard deviation increase in the innovation index comprises a 34% increase for industries that more intensely use the local university's innovation. On the other hand, when this change is viewed relative to the standard deviation of 20 year employment growth, it looks much smaller: $34/740 = 5\%$. The large standard deviation is due to the skewness of the data; some very large county-industries raise the measure of dispersion. Yet another way of scaling the coefficient is per university patent affecting an industry; with this metric, the magnitude of the 20 year effect is about 15 workers per patent in each county proximate to the university in which it was produced.

from 1977-1997 in the Annual Survey of Manufacturers.

5.6 Knowledge Spillovers and Localization of Growth Effects

All results thus far have been estimated allowing all counties within a 75 mile radius of a university to be “treated” by it. To understand the role of proximity in the spread of knowledge from universities to industry, I now zoom in on the area around the university by limiting the reach of university treatment to only counties *containing* universities. Estimates for the same basic equations, but with the narrowed treatment, are displayed in row 1 of Table 5. Estimates using the 75 mile circle treatment are reproduced in row 2 for comparison. Effects sizes are significantly greater when the focus of the estimation is narrowed around university campuses: for a standard deviation increase in the innovation index, employment rises by 59 workers per county-industry in “containing” counties but only by 31 workers in all “75 mile circle” counties. There is also a greater positive effect on number of establishments in containing counties and a smaller increase in average establishment size. These last two effects could reflect increased spinoff activity in the areas immediately surrounding universities. All of these differences in estimates between rows 1 and 2 indicate different treatment effects of high innovation index versus low innovation index industries within a county depending on how close that county is to the university. This evidence suggests that proximity facilitates the spread of knowledge and supports the importance of knowledge spillovers as an agglomeration economy that promotes the growth of industrial clusters.

The amount of people to talk to and learn from in a place also appears to encourage the spread of knowledge. Table 6 shows that the effect of university innovation scales with initial county employment. 1977 county employment here is measured in thousands of workers, so the coefficient in column 1 indicates that an additional 100,000 initial workers corresponds to an additional 17 workers from a standard deviation increase in university innovation. The effect of universities on payroll and average establishment size also scales with initial city size. Because city size tends to be highly correlated with the density of city centers, this result supports the idea that density encourages growth from knowledge spillovers, as the basic theory on agglomeration suggests Marshall (1890).

5.7 Growth from Federal Research Funding

Results shown thus far use the scale and relative intensity of university innovation in different technological areas as the source of cross-sectional variation. I now turn to estimating the effect of universities on local employment growth using a different source of variation: the amount of federal research funding received by university campuses in the five years before Bayh-Dole. Universities that received more funding before the law was passed would have had more research suddenly opened to commercialization, and the areas around them might be expected to experience a larger stimulative effect.

Table 7 presents estimates using total federal funding, total Department of Defense (DOD) funding, and total National Institutes of Health (NIH) funding. The latter two subcategories may more closely track dollars for practical research likely to influence industry. Indeed, the coefficients on the interaction term – the product of an indicator equalling one after Bayh-Dole and the five year pre-Bayh-Dole sum of funding – are all positive and significant, with stronger effects for DOD and NIH funding in particular. An area that received an additional \$10 million in DOD or \$7 million in NIH funding before Bayh-Dole received an additional worker per county-industry after 1980. This effect is the average over all economic census years through 1997, so it is an average long-term effect of initial funding. These positive employment effects from government research spending can be taken into consideration in addition to the health and national security advances that would generally be viewed as the primary economic benefits of government spending from these agencies.

6 Endogeneity Concerns and Robustness

6.1 Endogeneity of university innovation

There are several endogeneity concerns to keep in mind when considering these results. The biggest concern, and the one around which the empirical strategy is designed, is the endogeneity of university research agenda to local industry activity. This concern has two sources: pre-treatment trends and measurement.

6.1.1 Pre-treatment trends

Though the core strategy of combining a shock with cross-sectional variation aims to isolate the effect of universities on industry, it leaves open the possibility that employment was growing differentially across industries and space before Bayh-Dole in such a way that it both predicts the technological fields of university innovation and continues in a similar manner after the law. In other words, this argument is that there were pre-existing industry growth trends, not having to do with university research, that continued after Bayh-Dole and explain the measured effect. In the LBD data, which is left-censored in the pre-Bayh-Dole period, I cannot measure the pre-treatment trends necessary to completely rule out this possibility. Of course, for this confound to explain my result, a very particular type of differential pre-trend would need to have existed: specifically, the industries I measure to be most affected by universities would need to have been growing faster than others in that area before the law. Which industries grew quickly before the law would also need to have differed across geographical areas according to the strengths of the nearby university.

Nevertheless, I further investigate the possibility of differential pre-treatment trends using publicly available County Business Patterns (CBP) data. These data are far from ideal, as they are heavily censored for confidentiality: 30% of employment observations are censored in 1972, and 70% are censored in 1977,⁴⁴ the two economic census years relevant for measuring pre-treatment trends. Before running a pre-trends regression, I assess whether the censoring of the data is essentially random with respect to my cross sectional treatment, the innovation index. To do so, I regress an indicator for whether employment in a county-industry is censored on the treatment, allowing the effect to be different in 1972 and 1977. In both years, the innovation index significantly and positively predicts censoring, but there is no significant difference between the two years. That censoring is non-random with respect to my treatment implies that any regression run with the censored data will be biased. Furthermore, that treatment predicts the county-industries that will be too small in 1972 and 1977 to have employment numbers reported implies that the industries and places predicted to be stimulated by university innovation after Bayh-Dole in fact were systematically smaller before the law. That there was no significant difference between 1972

⁴⁴A higher percentage of the data is censored in 1977 simply because four times as many observations exist in the first place; reporting standards changed between 1972 and 1977 such that any county-industry with at least 50 employees – rather than at least 100 employees – would now appear in the data. In other words, similarly large amounts of employment information is missing in both years.

and 1977 quite importantly implies that those industries were also not yet growing systematically faster than other industries and places. Finally, on data aggregated to the two-digit SIC level, I run the formal regression to assess pre-treatment trends and find that the trend is not statistically significantly different from zero. This result holds whether or not employment is imputed for censored county-industries.⁴⁵

6.1.2 Measurement of universities' innovative strengths

One might also be concerned that my index measure of innovation, which provides between-industry identification, picks up endogenous research activity of universities because it uses patents granted until 1985. Ideally the measure would use patents granted only through 1980 to capture innovation that was truly exogenous to the Bayh-Dole Act of December 1980, its follow-on Trademark Clarification Act of October 1984, and their associated stronger connections between universities and industry. However, because university patenting was considerably more sparse before the law, it would be difficult to accurately measure universities' innovative strengths with pre-1981 patents; using additional years of observed patent production improves measurement. Patents until 1985 are still arguably exogenous to the biggest effects I find, which don't hit until 1992 and 1997. Furthermore, given patent application-to-grant lags of at least 2-3 years and plausible research lags, any patents granted by 1985 undoubtedly came from research projects conceived before Bayh-Dole and certainly before the legislation was completed at the end of 1984.

6.2 Sensitivity

6.2.1 Model choice and outliers

The results are not driven by arbitrary estimation choices. Positive and significant effects are also present for quantile regressions at the 50th and 75th percentile. Outliers at the top of the employment growth distribution can be removed without eliminating the effect. Removing "zero" observations by reducing the number of "potential entrant industries" included in the data only

⁴⁵Employment can be imputed for censored county-industries in the CBP using the number of establishments in each establishment size category and multiplying by the midpoint of the employment range for the category, as done in Glaeser et al. (1992).

strengthens the effect.⁴⁶

6.2.2 Generality of effect

An important consideration in understanding these effects is whether they are driven by a few top universities and their associated innovative clusters, or whether the university effect is found nationwide around innovative universities. To investigate this question, I re-run the estimation without two major hotbeds of innovative activity: Silicon Vally and Boston’s Route 128 corridor. Excluding Massachusetts and California from the estimation sample results in only a 4 employee reduction in the 31 worker university effect per standard deviation increase in the innovation index.⁴⁷ Other results are similarly little-altered by the exclusion. It appears that the local economic effects of universities are important nationwide.

6.2.3 Universities as fortuitous betters

The possibility that universities simply produced innovation in the nation’s most quickly growing industries, such as biotech, also cannot explain the effect. Employment and payroll growth effects remain strong even when industry-by-year fixed effects are included to account for nationwide changes in industry performance.

6.2.4 Cross-area differences and endogeneity of federal funding

Estimation of the effects of federal funding on subsequent employment has more potential confounders because funding varies at the county, not industry, level, and so estimation relies on comparing the growth of one county to that of another. Thus any shocks that affect areas differently could potentially bias the result. If areas with highly funded universities also disproportionately experienced other positive economic shocks, my estimates of the funding effect would be biased upward. It could also be that areas with highly funded universities were trending differently before Bayh-Dole; if those areas were already growing faster beforehand – something I would not be able to observe in LBD data – I may attribute too much of their subsequent growth to Bayh-Dole and

⁴⁶See section IV.E. describing the main data sample for a more complete discussion of “potential entrant industries” and accounting in estimation for entry.

⁴⁷31 workers per county-industry is the coefficient from the specification with industry-by-year fixed effects in Table 2, column 2.

federal research funding. Of course, these concerns do not apply to the main analysis, which uses variation within counties and controls for differences and differential shocks between geographic areas.

6.2.5 Timing

Finally, the timing of effects may raise concern that something other than universities generated this 20 year growth.⁴⁸ I find the largest growth effects in 1992, such that several years elapsed during which university-industry dynamics could have evolved. I argue, however, that the dynamic effects of stronger university-industry connections in the years after Bayh-Dole are an important part of what I seek to measure. In addition to being able to measure an immediate effect in the partial equilibrium sense of a difference-in-differences analysis, I am able to measure the long-run effects of a major change in the relationship between universities and industry. Though significant effects were apparent very soon after the law as commercialization began to rise, university-industry connections snowballed and the initial growth dynamics continued as universities adjusted their commercialization infrastructure to the new innovation environment.

7 Mechanisms of the University Effect

Two central goals of this paper are to provide plausibly causal evidence that universities generate local economic growth, measuring the magnitude of the effect, and to provide evidence on our theories of knowledge spillovers as an important source of agglomeration economies. Results presented so far have spoken to both of these issues. Universities generate economically important employment and wage growth in their local areas, and these effects strengthen both with city size and with proximity to the university, suggestive of the role knowledge spillovers. To gain a deeper understanding of this effect, it makes sense to get a sense of the mechanisms through which university innovation creates growth. First, plausible mechanisms can boost our confidence that the measured result is real, and not spurious. Second, they can further support – or discredit – the notion that local knowledge spillovers play an important role, and thus inform our models of

⁴⁸One might actually expect delayed industry effects of research, which takes time to produce, to disseminate, and potentially to develop further into a usable or marketable product. On a national level, in highly aggregated industries, Adams (1990) finds lags of approximately 20 years between the appearance of academic research and industry productivity gains.

agglomeration. And third, they can heighten the usefulness of the result to policy-makers trying to design a set of policies to harness their local university’s stimulative power.

The results in this section provide evidence on the way in which the university growth effect operates. Because entrepreneurs – a group which can potentially be defined in multiple ways – are a continual focus of academic and policy debates on the drivers of growth in general, and growth from universities in particular, I first evaluate in section 7.1 the extent to which they may drive industry growth from university innovation. I find that whether “entrepreneurs” are defined by their size or by their age, they are not directly responsible for the brunt of the employment growth from universities. Entrant establishments to the university area and related industries after Bayh-Dole are crucial, but those that bring the most employment tend to be expansions of existing, multi-unit firms.

Having identified the primary industry drivers of the university growth effect, I then turn in section 7.2 to detailed, confidential Census Bureau data on firm R&D activity to corroborate the evidence. If large, multi-unit expansions to university areas and industries after Bayh-Dole are indeed responsible for the majority of the employment growth, then we would expect these entrant establishments to be the ones most likely to engage in joint projects with universities, to transfer intellectual property across entities, and to produce, in turn, their own innovation. The evidence I provide supports this mechanism and the importance of local knowledge flows between universities and these establishments.

7.1 Evaluating the Role of Entrepreneurs

Do universities generate employment growth from entrepreneurs or from existing powerhouses? Numerous claims are launched regarding the important contribution of entrepreneurs – new or small firms – to job creation. SBA Administrator Karen Mills asserted in May 2010 that “small businesses create about 2 of every 3 new jobs in America each year,” and “drive American innovation and competitiveness.”⁴⁹ Recent empirical evidence, however, indicates that new – but not necessarily small – firms are responsible for much of the nation’s year-to-year net job creation (Haltiwanger et al. (2013)). The extent to which these types of establishments, as purported innovators, drive

⁴⁹See Davis et al. (1996) for a collection of claims made by politicians and the Small Business Administration on the importance of small businesses in generating employment growth and other positive outcomes.

the long-run employment growth effect from university innovation is unknown. Being flexible with the definition of “entrepreneurs,” I consider establishment heterogeneity along two dimensions – incumbency status and size – and evaluate whether entrepreneurs by either of these definitions seem to drive employment growth from universities. Existing theoretical and empirical evidence present arguments both for and against the importance of entrepreneurs in this context.

While entrants may be highly innovative, engendering market change at the expense of competitors, incumbents may be entrenched, in good position to fend off young firms and continue to grow. In particular, they may have established relationships with universities – useful when navigating bureaucracy and administrative hassle in technology transfer – as well as established systems for commercializing products: manufacturing expertise, distribution channels, and brand name, all of which may help to preserve power. Some theories of innovation and growth further predict that innovating entrants may spur technologically advanced incumbents to compete while forcing laggards into decline, generating a bifurcated effect among existing firms (Aghion et al. (2005, 2009)). These theories stress the importance of entrants and of the weeding out of less productive incumbents.

To empirically evaluate the relative importance of incumbents versus entrants, I decompose the total twenty year growth effect from universities into three well-defined groups of establishments: 1) surviving incumbents: those that existed in 1977 and were still alive in 1997, 2) dying incumbents: those that existed in 1977 and exited before 1997, and 3) entrants: those that entered after 1977 and were still alive in 1997.⁵⁰

Row 1 of Table 8 presents the results of this first dimension of decomposition. Cells in columns 1-4 contain coefficients on the innovation index in regressions predicting 1977 to 1997 employment change for the establishments in that group. Each coefficient thus represents the treatment effect of university innovation on that type of establishment. The coefficient of 43.72 in column 1, row 1 is the total 20 year growth effect for a standard deviation increase in the innovation index.⁵¹ Moving across columns in the top row, one can see that the entrants, with a coefficient of 46.26 (column 4, row 1), dominate incumbents in contributing to the total growth effect; the coefficients for the

⁵⁰Establishments that both entered and exited during the period did not contribute to the net effect and are omitted from this part of the analysis.

⁵¹This is the coefficient from a regression of (emp97 - emp77) on the innovation index with county and year fixed effects but no industry-by-year fixed effects.

two incumbent groups, 19.66 and -22.2, sum to essentially 0 net incumbent growth. The negative coefficient for dying incumbents and the positive coefficient for surviving incumbents indicate that among existing establishments, those in industries more closely connected to university innovation actually experienced more turnover than did others, as some establishments shed substantial employment and others added it. Taken together, these results suggest a “creative destruction” effect in these innovative industries, consistent with the Aghion et al. (2005, 2009) models. Some incumbents may respond to new competition by innovating and growing while others, perhaps the less efficient establishments, are forced out.

But the large growth contribution of entering establishments requires refinement: not all entering establishments fit our standard notion of small entrepreneurial ventures. While some entering establishments are single-unit firms - i.e. the entering establishment is an entering firm - others are expansions of existing multi-unit firms. Table 9 decomposes the entering establishment effect into that from single-unit entry versus that from multi-unit expansion. Row 1 indicates that when all establishment sizes are pooled, multi-unit expansions contribute approximately 2.5 times the employment growth of single-unit entrants. Moving down each column, the pooled effects are broken down by establishment size at time of entry to the geographic location; unsurprisingly, among small establishments, single-unit entrants drive the employment growth effect, while among large entering establishments, multi-unit expansions dominate single-unit entrants. The results of Tables 8 and 9 together indicate that the employment growth effect from university innovation is driven by entrant establishments and in particular by large, multi-unit expansions into the areas near universities.

How small versus large firms, more generally, figure into the dynamics of innovating industries is also a subject of considerable theoretical and empirical focus. Small firms, and university spinoffs in particular, are often considered to be drivers of growth (Shane (2004a)), but their systematic impact on the economy is uncertain because it is difficult to track firms that use university ideas and to measure their importance relative to other firms.⁵² Small firms, and the inventors within them, may have the advantage of freedom to explore new and risky ideas (with potentially high payoffs)

⁵²An advantage of the methodology and data used in this paper relative to existing literature is that they allow tracking of employment gains for firms of all sizes that are likely to use the nearby university’s ideas. Of course, the spillover benefits of each of these types of firms on others are likely also to be economically important. Hausman (2017) measures local spillovers from establishments of different sizes.

that large firms may avoid in favor of focusing on more immediate market rewards, potentially by buying innovations of known quality from outside the firm (Acemoglu (2009)). The small firms may also be more inclined towards work – like early idea development – that doesn’t require expensive infrastructure or that takes advantage of external infrastructure, like that in the university.⁵³ On the other hand, large firms may be better positioned to translate university innovation into economic growth given possible economies of scope (Arrow (1962)) or scale (Chandler (1990)) in innovation. In particular, large firms with many lines of business may be better able to self-insure against the riskiness of a new project or to use their vast resources to mass produce and market a newly developed or purchased product. It is an empirical question whether small or large firms are more complementary to universities in generating employment growth from research.

To address the roles of smaller versus larger establishments, the rows of Table 8 further decompose each group of incumbents and entrants by establishment size at entry. In columns 2 and 4, the larger establishments contribute most positively to that column’s total employment growth effect. The implication, here, that large establishments are complementary with university innovation is consistent not only with the broader theories discussed above, but also with anecdotal evidence from technology transfer officers that, while small firms often license and develop a technology initially, they then pass it off to large firms to be mass-produced and marketed. Large firms may be better equipped to exploit relatively developed university innovation and translate it into employment growth. Scientists, too, indicate that they often go directly to large firms with their discoveries, as large firms may be more able to incorporate new methodologies or research projects. The large firm advantage may include elements of both scale and scope.

Somewhat at odds with the conventional wisdom on small business and university spinoffs, small establishments treated by universities in these data contribute much less to absolute employment gains over the 20 year period than do large establishments. The smallest establishments, however, do contribute considerably in proportion to initial size; the treatment effect per standard deviation increase in the innovation index of 6.24 employees for entrants of the smallest size is much larger relative to their 1-25 employee base than is 24.50 relative to a 1000 employee base (Table 8, column 4, rows 2 and 5). High innovation index industries also experience entry of significant numbers

⁵³The tendency of small firms to lack infrastructure may make them more inclined to engage in joint projects with universities or other firms that do have infrastructure. This reasoning is one theoretical argument why small firms may generate more knowledge spillovers than large ones.

of small establishments; Table 10, which regresses the number of establishments in each group that entered since 1977 and survived until 1997 on the innovation index, indicates that a standard deviation increase in the innovation index generates an additional third of a small establishment (0.36) per county-industry that entered and survived but one one-hundredth (0.01) of a large entering establishment that survived to the end of the period. If each distinct firm is like a lottery ticket in the market of new ideas, then the large numbers of small firms born from university innovation could have relatively quite important growth effects, if only in the longer run as these ideas mature and their impacts are realized. Entering small establishments may thus play an important role in the innovation economy even if they are not the dominant contributors to the university employment growth effect in the short term.

7.2 Evidence on University-Industry R&D relationships

Results from the previous section indicate that most of the employment gains from university innovation come from multi-unit expansions of existing firms opening new, large establishments nearby the university. A potential complementarity between universities and large establishments is also suggested by the increase in average establishment size in local, university-related industries (Table 2, columns 3 and 4). Examples of this kind of local growth around universities can be found easily in the Boston metro area, where Novartis, Bayer, and many other biotech and pharmaceutical firms opened branches to be near Harvard Medical School and MIT. One of the world's largest concentrations of pharmaceutical companies is located in the Pennsylvania-New Jersey area right around the University of Pennsylvania, which is known for its "meds and eds."

To provide additional evidence on this mechanism of growth from universities, I take advantage of an additional, highly detailed data set in the confidential U.S. Census Bureau data on firms: The Business Research and Development and Innovation Survey (BRDIS). The survey provides information on the R&D activity of approximately 45,000 firms per year, sampling with certainty those that were known to have engaged in R&D in the prior year and with some probability the rest, in a stratified sampling methodology. Fortuitously for the study of university-industry relationships, the survey asks specifically about R&D activities conducted together with universities and asks firms to detail the nature of these relationships. It also measures innovative activity and transfer of intellectual property between entities, allowing us to study systematically the relationships between

joint R&D activities, IP transfer and use, innovation, and growth. I connect the firms in the survey to their establishments in the LBD to assess the extent to which the types of establishments that seem to drive the university growth effect actually engage in joint R&D with universities.

This analysis compares establishments that entered the geographical area of a university after the Bayh-Dole Act was passed in 1980 to those that entered before. Further, it uses the same innovation index used in the previous analyses to hold a geographic area and time period fixed, and compare the activities of firms in industries more versus less technologically connected to the nearby university's innovative strengths. If indeed the faster growth I measure in university-related industries after Bayh-Dole is driven by multi-unit firms expanding to the university area to take advantage of its ideas, then we would expect to see that these firms are more likely to report formal R&D relationships with the university.

The first test of this mechanism is presented in Table 11. On the left-hand side of the regressions in Panel A is a count of post Bayh-Dole entrants to the county-industry in each size category that report any formal R&D relationships with the university. These relationships include work with academic consultants, work with interns or post doctoral researchers, sending employees to work in-house at a university laboratory, giving gifts to the university for research, defining the primary aim of the company as commercializing a university discovery, engaging this year in a new R&D agreement with a university, and spending some R&D funding on joint agreements with a US university. On the right-hand side is the innovation index, which, as before, varies at the county-industry level and measures the degree of technological connection of the industry to the local university. The regression is cross-sectional, with county-industry level observations and both county and industry fixed effects to control for location-specific and industry-specific factors that are unrelated to the university effect. The positive and significant coefficient on the innovation index in column 1 indicates that, in industries more closely connected to the local university, substantially more entrants to the area engaged in joint R&D with the university. Column 6 of Panel B, however, shows that in an analogous regression for pre-Bayh-Dole entrants to the county-industries near universities, no such relationship across local industries exists. This result suggests that the "treatment effect" of university innovation on industry worked primarily after Bayh-Dole, as we would predict: only then are entrant firms in local-university-related industries more likely to have university R&D relationships. Additionally, a comparison across columns of Panel A indicates

that this effect is driven by large firms and is non-existent for the smaller ones, lending support to the mechanism of large, multi-unit expansions suggested by the analysis of the previous section.

Table 12 breaks the effect down by type of relationship with the university so that we can understand the types of interactions that are likely to generate knowledge spillovers and, eventually, growth. The strength of the effect varies somewhat, but it is strongly positive and significant for firms reporting work with academic consultants, work with post doctoral researchers, sending a company representative to work in-house in a university laboratory, and having a formal joint R&D agreement with a university. All of these activities are likely to facilitate knowledge flows between universities and firms. Again, for each of these activities, the relationship does not hold for firms that opened an establishment in the university area before 1980, supporting the role of Bayh-Dole in encouraging university-industry connection.

Notably, the differential effect across industries does not hold for firms who report their primary aim as commercializing a university discovery (columns 4 and 9). Most likely this absence of an effect is due to the fact that small firms, like spinoffs, are the ones most likely to report commercialization as a primary aim, while the main university-connection effect I find is driven by large firms, which generally have many aims.

Of course, we would ideally like to be able to trace university ideas through a joint R&D relationship or knowledge sharing agreement with a firm to that firm's own innovative output. While even the BRDIS does not trace knowledge flows at the idea-specific level, it does measure IP transfer as well as innovation. Table 13 presents evidence that post-1980 entrants to the university area engage in more IP transfer in industries more technologically connected to the local university. They are more likely to either transfer IP to a spinout or receive IP as a spinout, to obtain a substantial financial interest in another company for the purpose of acquiring its IP, and to engage in free IP transfer between parties (columns 1, 2, and 3). These effects do not exist in any remotely similar magnitude for firms that entered the university area before 1980 (Panel B). That firms in these industries engage in IP transfer is encouraging if we are to believe that they're generating growth from university ideas.

And indeed, post-1980 entrants in these industries do generate more innovation, by several measures. Table 14, Panel A shows that these firms systematically produce more patent applications, granted patents, new goods, new services, and new manufacturing methods. Pre-1980 entrants to

university areas do not systematically differ between more and less university-related industries in their innovative output along these measures (Panel B).

Overall, the results from the BRDIS data provide strong support for the growth mechanism suggested by the decomposition results in section 7.1. Large, multi-unit expansions to the geographic area of a university and industries technologically connected to the university account for the lion's share of the university growth effect. The evidence presented suggests that these firms – in university-related industries and expanding to locate nearby them after Bayh-Dole – are also the ones most likely to engage in R&D relationships with universities, to engage in intellectual property transfer, and ultimately to produce innovation of their own.

8 Conclusion

I measure the effects of university innovation on local employment and payroll growth using a new identification strategy and detailed data, which allow tight geographical and technological links between universities and industry outcomes. I find that employment, average establishment size, payroll, and wages grew differentially more after the Bayh-Dole Act of 1980 in industries more closely related to innovation produced by the local university or research hospital. My best estimate of the total employment growth effect from universities over the 20 year period from 1977 to 1997 is approximately 34 workers per county-industry for a standard deviation increase in the innovation index, or 15 workers per county-industry per effective patent, off a base of about 100 workers per county-industry. The impact of universities increases with proximity to a university and with initial county size, supporting the importance of spatial relationships in the flow of knowledge. Overall, these results indicate that the increase in university connectedness to industry under the new incentives of the intellectual property regime created by Bayh-Dole produced important local economic benefits. The local nature of the effects reflects some combination of 1) changing university attitudes towards disseminating research to industry contacts, which may tend to be disproportionately local because of the greater ease of transferring complex knowledge in person, and, 2) complementarities between codified (e.g., patented) and non-codified (oral/tacit) knowledge.

Federal funding of university research also seems to stimulate local employment growth: an additional \$10 million of DOD funding or \$7 million of NIH funding to universities in the five years

before Bayh-Dole generated an additional worker per county-industry after 1980. Local growth effects are only one of multiple economic benefits that may be used to evaluate the large amounts of federal money – \$6.2 billion in 1971 and \$23.8 billion in 2007 – devoted to university research in the sciences.⁵⁴ And of course, such local employment effects from NIH and DOD spending may still be small compared to the primary benefits in health or national security, for example, that come from associated knowledge advancement.

The mechanisms through which local university effects operate have both intuitive and surprising components. Supporting the view of entrants as engendering change and driving economic progress, entering establishments to the university area over the period from 1977 to 1997 more than account for the full 20 year growth effect, while establishments incumbent to the university area have an insignificant contribution, as a whole, to growth: some die off as others compete and grow. The greater turnover in industries most closely tied to university innovation may reflect a sort of creative destruction induced by universities' technological progress. But the high-employment-growth establishments entering the geographic vicinity of the university tend to be expansions of incumbent firms already located elsewhere, rather than new firms that satisfy our typical image of entrepreneurs. These establishments are large at entry, bringing large numbers of new jobs immediately, and they add substantial employment over time. This pattern is strongly suggestive of large, incumbent firms realizing great benefits from locating near a university and benefitting both directly from its innovation and likely also indirectly from the large numbers of small spinoffs that exist in its immediate vicinity and can be acquired for growth.⁵⁵

Evidence from detailed U.S. Census R&D data lends substantial support to these mechanisms, showing that large, multi-unit expansions to the university area after 1980 are also the most likely to engage in joint R&D activities with the university, to transfer IP whether via formal payments or for free, and to produce innovation of their own. With this evidence, one can thus trace the path of ideas from universities to industry growth.

⁵⁴Funding amounts are aggregates from the NSF Survey of Federal Science and Engineering Support to Universities, Colleges, and Nonprofit Institutions, reported in 2005 dollars.

⁵⁵Large firms may be attracted to university areas in part for the ready availability of small firms to acquire. This paper does not diminish the role of those small firms, but rather emphasizes that the majority of the employment gains and formal university relationships come from the larger ones. Policy-makers who would like to encourage growth from their local university should thus consider policies to boost entrepreneurship but also those that might attract larger firms. Greenstone et al. (2010) shows that attracting large firms to a local area, irrespective of universities, can have significant spillover growth effects.

Numerous underlying economic characteristics of localities, from the degree of competition between firms to job mobility to a skilled population, have been shown to affect an area's subsequent growth.⁵⁶ Universities hold an important place among these factors both because of their core mission as producers and transmitters of new ideas – which economists have long considered crucial for sustained economic growth – and because of the control policy-makers may potentially wield over their operations. My evidence indicates that universities have important growth effects on their local economies, that local knowledge spillovers seem to play an important role in the capitalization of university ideas. Although entrepreneurs and university spinoffs may indeed be significant links in the commercialization chain, the importance of large firms cannot be ignored.

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⁵⁶See, for example: Glaeser et al. (1992, 1995); Glaeser and Kerr (2009); Glaeser et al. (2010); Agrawal et al. (2010); Doms et al. (2010); Fallick et al. (2006); Chen et al. (2010) for explorations of various factors of local growth.

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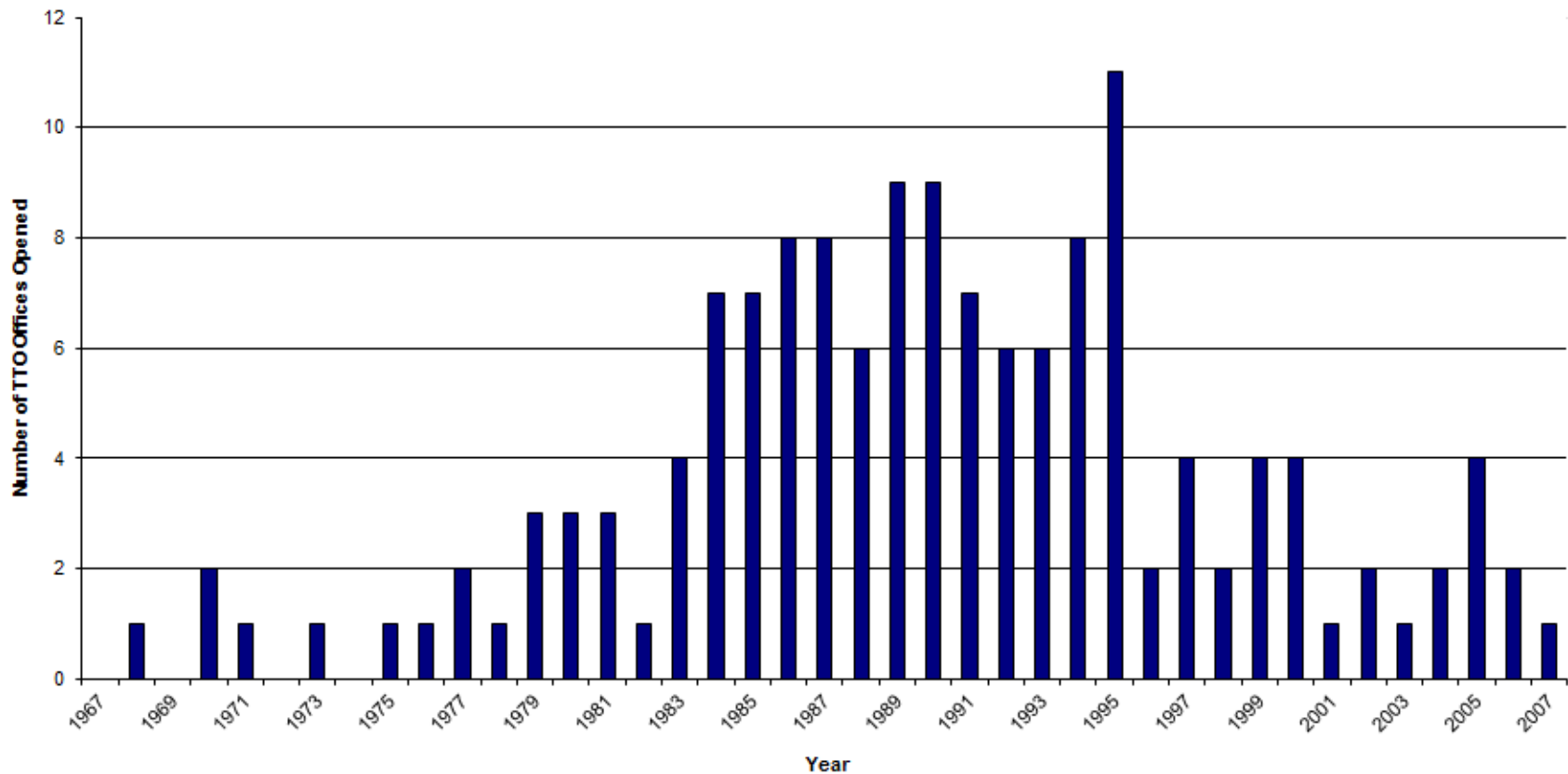
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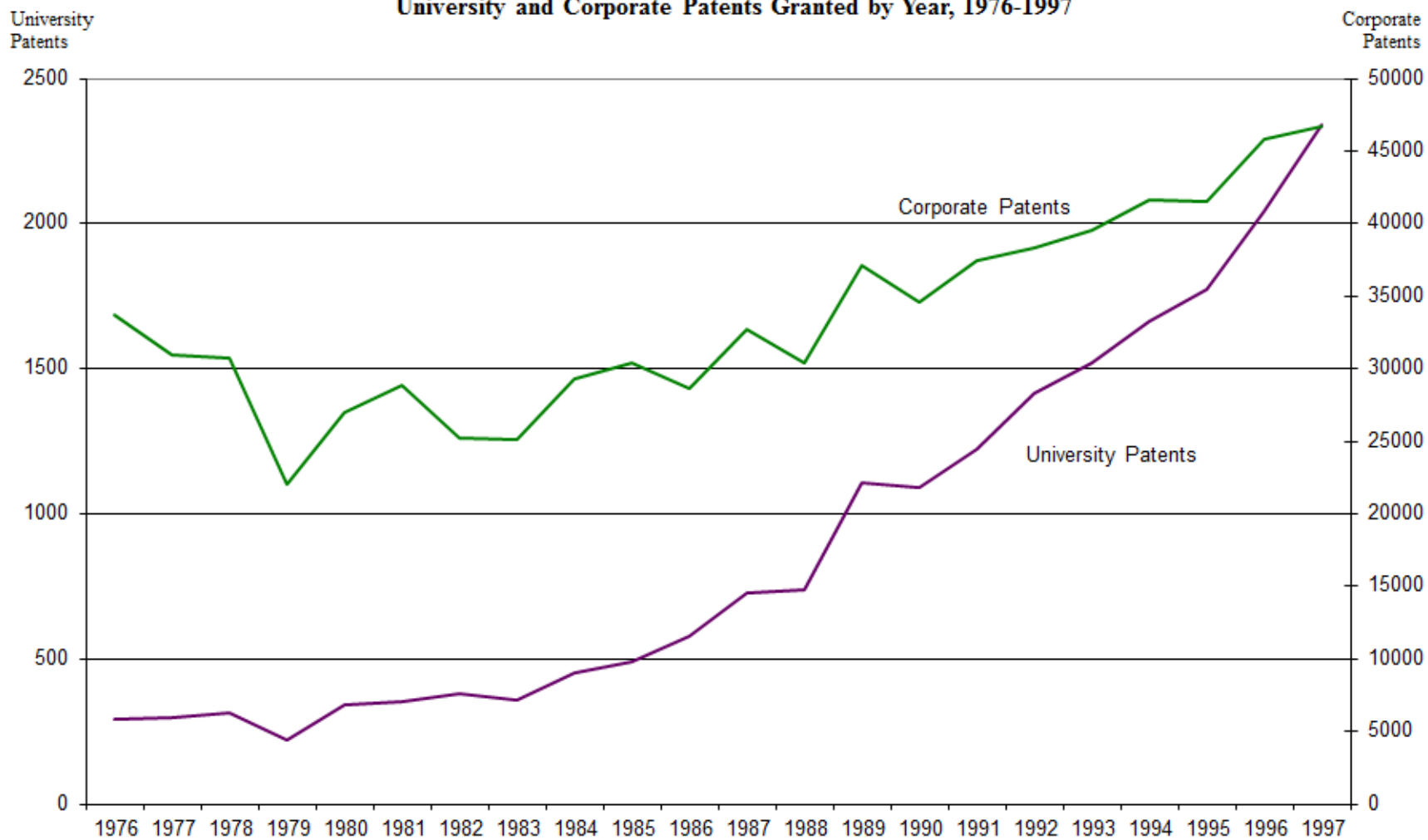
FIGURE 1
Openings of University and Hospital Technology Transfer Offices
1967 - 2007



Source: Association of University Technology Managers (AUTM) Licensing Activity Survey, 2007.

Note: Bars represent the number of university technology transfer offices (among AUTM members) opened in each year from 1967 to 2007.

FIGURE 2
University and Corporate Patents Granted by Year, 1976-1997



Source: National Bureau of Economic Research Patent Data.

FIGURE 3
Construction of the Innovation Index from Patent Data and a
Probabilistic Concordance

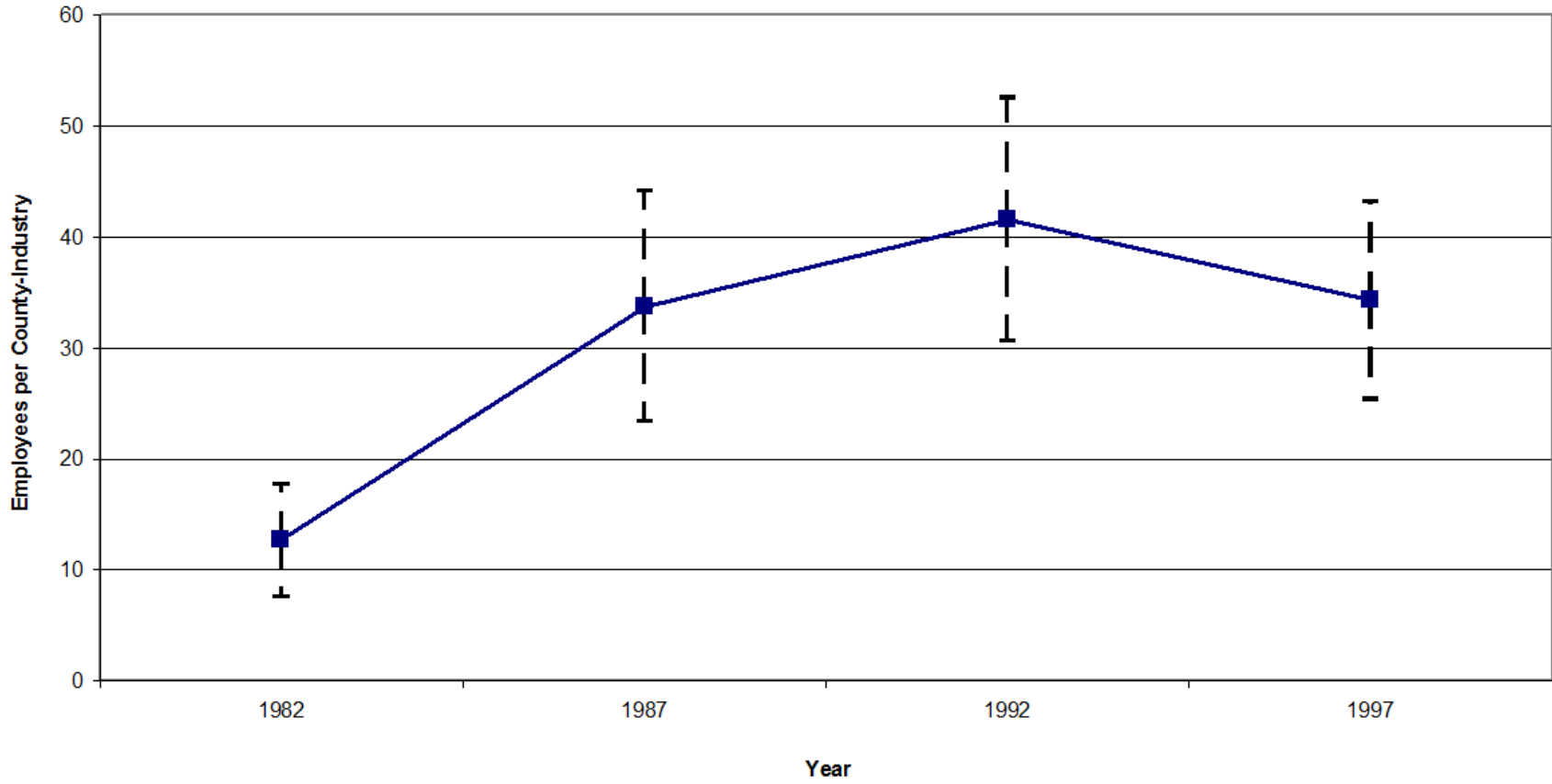
Concordance							
Patent Class	SIC3	weight	Example:	SIC3	weight	calculation	
12300	111	0.20	University A	111	0.40	= 2*0.20 + 1*0.00	
	222	0.00		222	0.05	= 2*0.00 + 1*0.05	
	333	0.20		2 x 12300	333	0.80	= 2*0.20 + 1*0.40
	444	0.45		1 x 12301	444	1.00	= 2*0.45 + 1*0.10
	555	0.15		555	0.75	= 2*0.15 + 1*0.45	
12301	111	0.00	sum of weights = 3				
	222	0.05					
	333	0.40					
	444	0.10					
	555	0.45					

Notes:

This figure provides an example of how the innovation index measure is constructed. The concordance on the left shows two patent classes and corresponding weights for all five SIC3 industries, even industries that have zero weight for a given patent technology class. Weights sum to 1 across SIC3s for each patent class.

If University A has two patents of the first class and one of the second, its innovation indices are calculated as shown at right. It ends up with a weight for every SIC3 industry. Because University A has 3 total patents, the sum of its innovation indices (before standardization for regressions) is 3. Thus this measure captures both the scale and the relative intensity with which a university innovates in different technological areas.

FIGURE 4
Employment Effects by Year After Bayh-Dole
1982 – 1997



Notes: Points represent coefficients on the interaction term of the innovation index and year indicators from a regression predicting total employment in a county-industry-year, with county and industry-by-year fixed effects. Estimates for this regression are shown in Table 4, column 2. Error bands represent the 95% confidence interval around these point estimates.

FIGURE 5
Employment Growth Decomposition by Incumbency and Establishment Size

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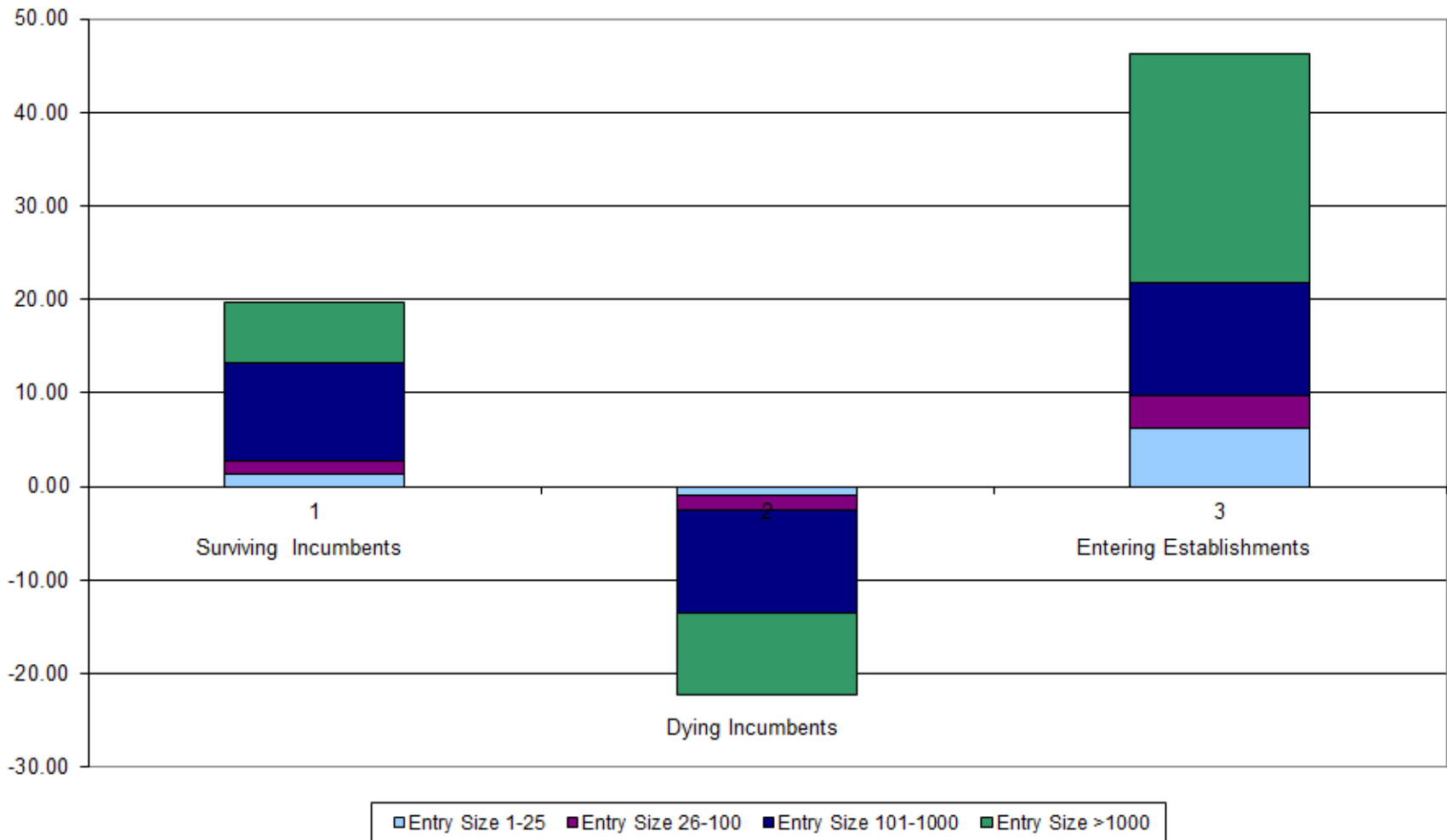


Table 1: Main Sample Descriptive Statistics

	Obs	Mean	Std. Dev.	Rounded Min	Rounded Max
Panel 1: All Census Years					
Total Employment	4,814,860	93.49	911.53	0	200,000
Total Emp, Univ Counties	3,723,200	103.77	1,008.72	0	200,000
Total Emp, Non-Univ Counties	1,091,660	58.41	439.05	0	150,000
Employment / # Establishments	4,814,860	13.06	128.88	0	30,000
Total Payroll (\$ thou)	4,814,860	3,131.09	164,662.00	0	280,000,000
Payroll per Worker (\$ thou)	4,814,860	11.02	438.51	0	800,000
Number of Establishments	4,814,860	5.01	40.90	0	10,000
Innovation Index	4,814,860	0.00	1	-0.089	100
Federal Research Funding, University Counties Only					
5 Yr Sum of Total Funding (\$m)	4,814,860	160.52	326.20	0	2,400
5 Yr Sum of DOD Funding (\$m)	4,814,860	16.55	71.16	0	600
5 Yr Sum of NIH Funding (\$m)	4,814,860	62.67	144.18	0	950
Panel 2: University Counties Only					
Δ Employment (97 - 77)	744,640	48.24	739.76	-70,000	100,000
Base Employment	744,640	103.79	921.21	0	200,000
Δ Emp (97 - 77) / Base Emp	340,837	0.53	1.35	-2	2
Panel 3: County Level Variables					
Total County Employment	15,370	30,918.86	121,380.50	0	4,000,000
Total County Employment, Univ Counties	8,950	45,973.15	155,172.90	0	4,000,000
Industries per County	15,370	330.18	146.70	1	400
Δ county employment (97 - 77)	3,074	13,399.47	46,807.55	-100,000	900,000

Notes:

¹ Observations are a county-industry-year. Panel 1 includes all five census years between 1977 and 1997. Panel 2 describes the total 1977 to 1997 change in employment.

² The innovation index measures the extent to which an industry is likely to be affected by innovation produced at nearby universities. It has been standardized to have mean 0 and standard deviation 1. For details on how this variable is constructed from the technology classes of university patents, please refer to the Data section of the text.

³ Base employment is defined as the average of 1977 and 1997 employment in a county-industry.

⁴ Following Census Bureau rules, mins and maxes are rounded to preserve the confidentiality of establishments.

Table 2: University Innovation and Related Industry Employment

	(1)	(2)	(3)	(4)
	Total Employment		Avg Establishment Size	
Innovation Index	51.86*** [6.61]	48.3*** [7.36]	6.6*** [0.46]	3.769*** [0.383]
After Bayh-Dole \times Innovation Index	38.73*** [4.66]	30.51*** [4.28]	3.15*** [0.26]	1.697*** [0.264]
County \times Year Fixed Effects	Yes	Yes	Yes	Yes
Industry \times Year Fixed Effects		Yes		Yes
Observations	4,814,860	4,814,860	4,814,860	4,814,860
R-squared	0.12	0.12	0.015	0.05

Notes:

¹ * significant at 10%; ** significant at 5%; *** significant at 1%

² Robust standard errors in brackets are clustered at the county level and adjusted for de-meaning where relevant.

³ An observation is a county-industry-year. All five census years from 1977-1997 are included.

⁴ After Bayh-Dole is an indicator equal to 1 after 1980.

⁵ The innovation index measures the extent to which an industry is likely to be affected by innovation produced at nearby universities. It has been standardized to have mean 0 and standard deviation 1. For details on how this variable is constructed from the technology classes of university patents, please refer to the Data section of the text.

Table 3: University Innovation and Related Industry Pay

	(1)	(2)	(3)	(4)
	Total Payroll (\$thou)		Wages (\$thou)	
Innovation Index	1,883.41*** [252.39]	1,807.87*** [282.5]	0.196*** [0.041]	0.065 [0.075]
After Bayh-Dole \times Innovation Index	1,831.26*** [253.89]	1,537.34*** [238.9]	0.222*** [0.038]	0.068 [0.092]
County \times Year Fixed Effects	Yes	Yes	Yes	Yes
Industry \times Year Fixed Effects		Yes		Yes
Observations	4,814,860	4,814,860	4,814,860	4,814,860
R-squared	0.0052	0.006	0.0002	0.0003

Notes:

¹ * significant at 10%; ** significant at 5%; *** significant at 1%

² Robust standard errors in brackets are clustered at the county level and adjusted for de-meaning where relevant.

³ An observation is a county-industry year. All five census years from 1977-1997 are included.

⁴ After Bayh-Dole is an indicator equal to 1 after 1980.

⁵ The innovation index measures the extent to which an industry is likely to be affected by innovation produced at nearby universities. It has been standardized to have mean 0 and standard deviation 1. For details on how this variable is constructed from the technology classes of university patents, please refer to the Data section of the text.

Table 4: Growth Effects by Year after Bayh-Dole

	(1)	(2)	(3)	(4)	(5)	(6)
	Total Employment		Total Payroll (\$thou)		Wages (\$thou)	
I{1982} × Innovation Index	16.81*** [2.81]	12.68*** [2.59]	337.79*** [102.29]	267.8** [107.87]	-0.013 [0.035]	0.126 [0.086]
I{1987} × Innovation Index	40.24*** [5.54]	33.74*** [5.30]	1,680.82*** [253.23]	1,426.47*** [257.39]	0.268*** [0.061]	-0.175 [0.200]
I{1992} × Innovation Index	51.81*** [6.00]	41.59*** [5.61]	2,481.50*** [306.64]	2,148.63*** [300.52]	0.407*** [0.046]	0.127 [0.087]
I{1997} × Innovation Index	46.62*** [5.07]	34.30*** [4.54]	2,858.06*** [467.03]	2,314.1*** [391.06]	0.342*** [0.095]	0.208 [0.096]
County × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year Fixed Effects		Yes		Yes		Yes
Observations	4,814,860	4,814,860	4,814,860	4,814,860	4,814,860	4,814,860
R-squared	0.12	0.12	0.0052	0.006	0.0002	0.0002

Notes:

¹ * significant at 10%; ** significant at 5%; *** significant at 1%² Robust standard errors in brackets are clustered at the county level and adjusted for de-meaning where relevant.³ An observation is a county-industry year. All five census years from 1977-1997 are included.⁴ The innovation index measures the extent to which an industry is likely to be affected by innovation produced at nearby universities. It has been standardized to have mean 0 and standard deviation 1. For details on how this variable is constructed from the technology classes of university patents, please refer to the Data section of the text.

Table 5: Growth and Proximity to the University

	(1)	(2)	(3)	(4)
	Total	Total Payroll	Avg	Num.
	Employment	(\$thou)	Establishment Size	Establishments
After Bayh-Dole \times Innovation Index (containing county only)	58.69*** [10.66]	2,943.63*** [491.20]	1.04*** [0.10]	0.202** [0.083]
After Bayh-Dole \times Innovation Index (all counties in 75 mile radius)	30.51*** [4.28]	1,537.34*** [238.9]	1.697*** [0.264]	0.158*** [0.032]
County \times Year Fixed Effects	Yes	Yes	Yes	Yes
Industry \times Year Fixed Effects	Yes	Yes	Yes	Yes

Notes:

¹ * significant at 10%; ** significant at 5%; *** significant at 1%

² Robust standard errors in brackets are clustered at the county level. An observation is a county-industry-year.

³ Each row in the table represents a separate regression, where the difference between the two regressions is only which counties are allowed to be “treated” by the local university’s innovation. The first row narrows the set of affected counties to just those containing an innovating university or hospital. For comparison, the second row shows coefficients from tables 1 and 2, in which all counties within a 75 mile radius of the university are allowed to be treated by the university.

⁴ After Bayh-Dole is an indicator equal to 1 after 1980.

⁵ The innovation index measures the extent to which an industry is likely to be affected by innovation produced at nearby universities. It has been standardized to have mean 0 and standard deviation 1. For details on how this variable is constructed from the technology classes of university patents, please refer to the Data section of the text.

Table 6: Knowledge Spillovers and City Size

	(1) Total Employment	(2) Avg Establishment Size	(3) Total Payroll (\$thou)	(4) Wages (\$thou)
After Bayh-Dole \times Innovation Index \times 1977 County Employment	0.171*** [0.017]	0.0021*** [0.000]	8.793*** [0.91]	0.0002 [0.0002]
County \times Year Fixed Effects	Yes	Yes	Yes	Yes
Industry \times Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	4,814,860	4,814,860	4,814,860	4,814,860
R-squared	0.142	0.015	0.0063	0.0002

Notes:

¹ * significant at 10%; ** significant at 5%; *** significant at 1%

² Robust standard errors are clustered at the county level and adjusted for de-meaning where relevant. An observation is a county-industry-year.

³ 1977 county employment is measured in thousands of employees.

⁴ After Bayh-Dole is an indicator equal to 1 after 1980.

⁵ The innovation index measures the extent to which an industry is likely to be affected by innovation produced at nearby universities. It has been standardized to have mean 0 and standard deviation 1. For details on how this variable is constructed from the technology classes of university patents, please refer to the Data section of the text.

⁶ Main effects of the Innovation Index and initial county employment are included in all specifications. Main effects of After Bayh-Dole are excluded because they are colinear with the county-year fixed effects.

Table 7: Federal Research Funding and Growth

	(1)	(2)	(3)
Dependent Variable: Employment	5 Yr Sum: Total Funding	5 Yr Sum: DOD Funding	5 Yr Sum: NIH Funding
After Bayh-Dole \times Fed Funding	0.061*** [0.012]	0.104*** [0.032]	0.140 [0.027]
County Fixed Effects	Yes	Yes	Yes
Industry \times Year Fixed Effects	Yes	Yes	Yes
Observations	4,814,860	4,814,860	4,814,860
R-squared	0.11	0.11	0.11

Notes:

¹ * significant at 10%; ** significant at 5%; *** significant at 1%

² Robust standard errors are clustered at the county level and adjusted for de-meaning where relevant. An observation is a county-industry-year.

³ After Bayh-Dole is an indicator equal to 1 after 1980.

⁴ Federal funding is measured in millions of dollars. The 5 year sum of federal funding includes the years 1976-1980, inclusive. Col. 2 uses the 5 year sum of funding from the Department of Defense. Col. 3 uses the 5 year sum of funding from the National Institutes of Health.

⁵ In all columns, the dependent variable is total employment in the county-industry-year, while the measure of federal funding changes across columns.

⁶ Main effects of Fed Funding are included in all specifications. Main effects of After Bayh-Dole are excluded because they are colinear with the county fixed effects.

Table 8: Growth in Entrants versus Incumbents

	(1) Δ Emp All Groups	(2) Δ Emp Surviving Incumbents	(3) Δ Emp Dying Incumbents	(4) Δ Emp Entering Establishments
All Establishment Sizes	43.72*** [4.95]	19.66*** [2.33]	-22.2*** [3.79]	46.26*** [6.47]
Entry Size 1-25		1.31*** [0.31]	-0.93*** [0.27]	6.24*** [1.32]
Entry Size 26-100		1.42*** [0.36]	-1.58*** [0.44]	3.53*** [0.87]
Entry Size 101-1000		10.44*** [1.02]	-11.09*** [1.90]	12.01*** [1.59]
Entry Size >1000		6.49*** [1.37]	-8.60*** [1.62]	24.50*** [3.88]

Notes:

¹ * significant at 10%; ** significant at 5%; *** significant at 1%

² Robust standard errors in brackets are clustered at the county level.

³ All cells are treatment coefficients from a regression of 1977 to 1997 change in employment in that establishment category on the Innovation Index.

⁴ Innovation Index measures the extent to which an industry is likely to be affected by innovation produced at nearby universities. It has been standardized to have mean 0 and standard deviation 1. For details on how this variable is constructed from the technology classes of university patents, please refer to the Data section of the text.

⁵ Entry size groups are assigned according to the size of the establishment in its year of entry. Because the data are left-censored, entry size for incumbents is defined as establishment size in 1977.

Table 9: Decomposing Entrant Growth -
Contribution of Single Unit Entrants and Multi Unit Expansions

	(1) Δ Emp All Entering Establishments	(2) Δ Emp Single-Unit Entrants	(3) Δ Emp Multi-Unit Expansions
All Establishment Sizes	46.28*** [4.48]	13.93*** [1.68]	32.32*** [3.63]
Entry Size 1-25	6.24*** [1.32]	5.15*** [1.09]	1.09*** [0.36]
Entry Size 26-100	3.53*** [0.87]	2.23*** [0.67]	1.30*** [0.27]
Entry Size 101-1000	12.01*** [1.59]	3.24*** [0.56]	8.76*** [1.10]
Entry Size >1000	24.50*** [3.88]	3.31*** [0.93]	21.17*** [3.43]

Notes:

¹ * significant at 10%; ** significant at 5%; *** significant at 1%

² Robust standard errors in brackets are clustered at the county level.

³ All cells are treatment coefficients from a regression of 1977 to 1997 change in employment in that establishment category on the Innovation Index.

⁴ The innovation index measures the extent to which an industry is likely to be affected by innovation produced at nearby universities. It has been standardized to have mean 0 and standard deviation 1. For details on how this variable is constructed from the technology classes of university patents, please refer to the Data section of the text.

⁵ Entry size groups are assigned according to the size of the establishment in its year of entry. Because the data are left-censored, entry size for incumbents is defined as establishment size in 1977.

Table 10: Effect of University Innovation on Numbers of Entrants,
by Establishment Size

	(1)	(2)	(3)	(4)	(5)
	All	Entry Size	Entry Size	Entry Size	Entry Size
	Establishment Sizes	1-25	26-100	101-1,000	> 1,000
Number of Entrant Establishments	0.43*** [0.10]	0.36*** [0.08]	0.03*** [0.01]	0.03*** [0.00]	0.01*** [0.00]

Notes:

¹ * significant at 10%; ** significant at 5%; *** significant at 1%

² Robust standard errors in brackets are clustered at the county level.

³ All cells are treatment coefficients from a regression of the number of entrant establishments in the respective size category on the Innovation Index. Entrant establishments are defined here as those who entered between 1977 and 1997 and still exist in 1997.

⁴ Innovation Index measures the extent to which an industry is likely to be affected by innovation produced at nearby universities. It has been standardized to have mean 0 and standard deviation 1. For details on how this variable is constructed from the technology classes of university patents, please refer to the Data section of the text.

⁵ Entry size groups are assigned according to the size of the establishment in its year of entry. Because the data are left-censored, entry size for incumbents is defined as establishment size in 1977.

Table 11: Pre- and Post-1980 Entry of Firms Reporting R&D Relationships with Universities by Firm Size

Panel A: Post-1980 Entrants Reporting any Formal Relationships with University					
	(1)	(2)	(3)	(4)	(5)
	All Firm Sizes	Firms of 1-10 Employees	Firms of 11-100 Employees	Firms of 101-1000 Employees	Firms of >1000 Employees
Innovation Index	0.073*** [0.013]	0.000 [0.001]	0.000 [0.001]	-0.002** [0.001]	0.076*** [0.014]
Constant	-0.680* [0.412]	-0.010 [0.006]	-0.010 [0.007]	-0.032** [0.016]	-0.630 [0.391]
County FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	459,081	459,081	459,081	459,081	459,081
R-squared	0.090	0.000	0.010	0.040	0.090
Panel B: Pre-1980 Entrants Reporting any Formal Relationships with University					
	(6)	(7)	(8)	(9)	(10)
	All Firm Sizes	Firms of 1-10 Employees	Firms of 11-100 Employees	Firms of 101-1000 Employees	Firms of >1000 Employees
Innovation Index	0.000 [0.002]	0.000 [0.000]	-0.000** [0.000]	-0.002*** [0.001]	0.000 [0.001]
Constant	-0.080 [0.070]	0.000*** [0.000]	0.000 [0.000]	0.000 [0.003]	-0.080 [0.062]
County FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	459,081	459,081	459,081	459,081	459,081
R-squared	0.070	0.000	0.010	0.020	0.070

Notes:

¹ * significant at 10%; ** significant at 5%; *** significant at 1%

² Robust standard errors in brackets are clustered at the county level.

³ Regressions are cross-sectional with observations at the county-NAICS-4 industry level. The dependent variable is a count of firms of the indicated firm size group that both entered a county-industry in the indicated time period and reported engaging in at least one of 8 types of R&D relationships with universities, as described in the text. The pre-1980 period includes 1980, as the Bayh-Dole Act was passed in December of that year. All regressions include county and industry fixed effects. Data on R&D relationships come from the Census' confidential Business Research and Development and Innovation Survey (BRDIS).

Table 12: Pre- and Post-1980 Entry of Firms Reporting R&D Relationships with Universities by Relationship Type

Panel A: Post-1980 Entrants Reporting each Formal Relationship with University					
	(1)	(2)	(3)	(4)	(5)
	Work with Academic Consultants	Work with Post Docs	Work as Visitor in University Lab	Primary Aim to Commercialize University Discovery	Joint R&D Agreement with University
Innovation Index	0.034*** [0.007]	0.063*** [0.012]	0.023*** [0.005]	0.000 [0.000]	0.013*** [0.002]
Constant	-0.392* [0.227]	-0.570 [0.375]	-0.170 [0.126]	-0.020 [0.014]	-0.159* [0.095]
County FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	459,081	459,081	459,081	459,081	459,081
R-squared	0.090	0.090	0.060	0.040	0.110
Panel B: Pre-1980 Entrants Reporting each Formal Relationship with University					
	(6)	(7)	(8)	(9)	(10)
	Work with Academic Consultants	Work with Post Docs	Work as Visitor in University Lab	Primary Aim to Commercialize University Discovery	Joint R&D Agreement with University
Innovation Index	-0.003** [0.001]	0.000 [0.001]	0.000 [0.001]	-0.001*** [0.000]	-0.004*** [0.001]
Constant	-0.060 [0.045]	-0.080 [0.061]	-0.020 [0.021]	0.000 [0.002]	-0.030 [0.020]
County FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	459,081	459,081	459,081	459,081	459,081
R-squared	0.050	0.070	0.020	0.020	0.080

Notes:

¹ * significant at 10%; ** significant at 5%; *** significant at 1%

² Robust standard errors in brackets are clustered at the county level.

³ Regressions are cross-sectional with observations at the county-NAICS-4 industry level. The dependent variable is a count of firms that both entered a county-industry in the indicated time period and reported engaging in the indicated type of R&D relationship with universities. The pre-1980 period includes 1980, as the Bayh-Dole Act was passed in December of that year. All regressions include county and industry fixed effects. Data on R&D relationships come from the Census' confidential Business Research and Development and Innovation Survey (BRDIS).

Table 13: IP Transfer, Industry Dynamics, and Knowledge Spillovers in Pre- and Post-1980 Entrants by Strength of Industry Connection to University

Panel A: Post-1980 Entrants			
	(1) Transfer IP to Spinout or Receive IP as Spinout	(2) Acquisition/Financial Interest for IP	(3) Allowed Free Access or Gained Free Access to IP
Innovation Index	0.073*** [0.012]	0.046*** [0.010]	0.151*** [0.027]
Constant	-0.490 [0.327]	-0.450 [0.298]	-1.040 [0.719]
County FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	459,081	459,081	459,081
R-squared	0.100	0.090	0.110
Panel B: Pre-1980 Entrants			
	(4) Transfer IP to Spinout or Receive IP as Spinout	(5) Acquisition/Financial Interest for IP	(6) Allowed Free Access or Gained Free Access to IP
Innovation Index	0.000 [0.001]	0.000 [0.001]	0.002* [0.001]
Constant	-0.050 [0.038]	-0.030 [0.023]	-0.070 [0.058]
County FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	459,081	459,081	459,081
R-squared	0.060	0.060	0.080

Notes:

¹ * significant at 10%; ** significant at 5%; *** significant at 1%

² Robust standard errors in brackets are clustered at the county level.

³ Regressions are cross-sectional with observations at the county-NAICS-4 industry level. The dependent variables in columns 1 and 4 are counts of firms entering the county-industry in the indicated time period who report having transferred IP to a spinout or received IP as a spinout from a parent company. The dependent variables in columns 2 and 5 are counts of firms entering the the county industry in the indicated time period who report having acquired a company or a financial interest in a company for the purpose of gaining access to their IP. The dependent variables in columns 3 and 6 are counts of firms entering the county-industry in the indicated time period who report having either accessed others' freely available IP or having allowed others to access their own IP for free. The pre-1980 period includes 1980, as the Bayh-Dole Act was passed in December of that year. All regressions include county and industry fixed effects. Data on IP transfer come from the Census' confidential Business Research and Development and Innovation Survey (BRDIS).

Table 14: Innovation from Pre- and Post-1980 Entrants
by Strength of Industry Connection to University

Panel A: Innovation from Post-1980 Entrants					
	(1)	(2)	(3)	(4)	(5)
	Patent Applications	Patents Granted	Introduced New Goods	Introduced New Services	Introduced New Manufacturing Methods
Innovation Index	128.048*** [21.689]	83.304*** [14.674]	0.150*** [0.026]	0.330*** [0.054]	0.157*** [0.027]
Constant	-769.290 [554.094]	-441.600 [325.516]	-1.160 [0.768]	-2.588* [1.452]	-1.210 [0.754]
County FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	459,081	459,081	459,081	459,081	459,081
R-squared	0.090	0.100	0.110	0.150	0.100
Panel B: Innovation from Pre-1980 Entrants					
	(6)	(7)	(8)	(9)	(10)
	Patent Applications	Patents Granted	Introduced New Goods	Introduced New Services	Introduced New Manufacturing Methods
Innovation Index	-0.660 [3.061]	-0.720 [1.355]	-0.005* [0.003]	0.000 [0.003]	0.000 [0.003]
Constant	-68.790 [54.999]	-36.880 [31.914]	-0.120 [0.089]	-0.120 [0.104]	-0.120 [0.093]
County FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	459,081	459,081	459,081	459,081	459,081
R-squared	0.050	0.050	0.090	0.050	0.050

Notes:

¹ * significant at 10%; ** significant at 5%; *** significant at 1%

² Robust standard errors in brackets are clustered at the county level.

³ Regressions are cross-sectional with observations at the county-NAICS-4 industry level. The dependent variables in columns 1, 2, 6, and 7 are counts of patent applications by and patents granted to firms entering the county-industry in the relevant time period. The dependent variables in columns 3-5 and 8-10 are counts of firms entering the county-industry in the relevant time period who report having introduced new goods, services, or methods of manufacturing to the market. The pre-1980 period includes 1980, as the Bayh-Dole Act was passed in December of that year. All regressions include county and industry fixed effects. Data on innovation activity come from the Census' confidential Business Research and Development and Innovation Survey (BRDIS).