THE VIRTUOUS CYCLE OF INNOVATION AND CAPITAL *

Naomi Hausman
Hebrew University

Daniel C. Fehder
University of Southern California

Yael V. Hochberg
Rice University & NBER

Current Version: August 12, 2023

Does local innovation attract venture capital? Using a regime change in the commercialization of university innovation in 1980 that strongly increased university incentives to patent and license discoveries, we document the complement to Kortum and Lerner (2000)'s finding that financing leads to future innovation. Because universities have different technological strengths, each local area surrounding a university experienced an increase after 1980 in innovation relevant to particular sets of industries which differed widely across university counties. Comparing industries within a county that were more versus less related to the local university's innovative strengths, we show that venture capital dollars after 1980 flowed systematically towards geographic areas and industries with the greatest sudden influx of innovation from universities. In contrast, the geographic and industry distributions of corporate patenting and prior venture financing in the pre-period do not predict a differential increase in future venture financing, suggesting that our findings are not solely driven by the 1979 pension fund reform that increased financing available to VCs across the board. The results support the notion of a "virtuous cycle" wherein innovation serves to draw capital investment that then funds future innovation.

JEL Codes: G24, R11, R58

---

* We thank Adam Jaffe, Josh Lerner, Alex Whalley, Olav Sorenson, Francisco Queiro, Noam Yuchtman, and workshop and conference participants at the American Finance Association, AIEA, Boston College, CREST, Hebrew University, Institute for Private Capital, NBER Entrepreneurship Working Group, University of British Columbia, University of Lausanne, University of Maryland, University of North Carolina Emergence Conference, UC Merced, UC San Diego, Sciences Po, Temple University, and Tel Aviv University for helpful conversations, comments and suggestions. Abigail Liu provided excellent research assistance. We are grateful for support from the US-Israel Binational Science Foundation (Grant 2016418). All errors are our own. Corresponding Author: Yael Hochberg (hochberg@rice.edu), Rice University, 6100 Main St. MS-531, Houston, TX 77005.

1. INTRODUCTION

Venture capital is a key input to innovation-driven entrepreneurship, and thus to economic growth (Botelho, Fehder, and Hochberg 2021). VC-backed firms constitute over 50% of initial public offerings on US stock markets (Kaplan and Lerner 2010), and regions and industries that receive more venture capital are more likely to see subsequent increases in regional patenting, employment, and aggregate income (Kortum and Lerner 2000; Samila and Sorenson 2010). The geographic distribution of venture capital and other forms of investment for innovation-driven entrepreneurship, however, is highly concentrated. In 2019, Silicon Valley firms received 39% of all U.S. venture capital (VC) allocations; the top three cities received 60% of all VC funding deployed; and the top five received 69% (PwC MoneyTree 2019). Lack of access to capital to grow innovative new companies is a frequently cited reason for some regions' less well-functioning entrepreneurial ecosystems, and it has been one of the most frequently targeted areas for policy intervention (Lerner 2009). Because VC funds invest disproportionately locally (Chen et al. 2010), understanding what draws VC funding to a region is important for understanding how and why entrepreneurial clusters form. In this paper, we show that VC itself is drawn to and deployed in a region in response to positive shocks to innovative activity. Our findings suggest the existence of a virtuous cycle of innovation and capital that serves as a critical component of successful entrepreneurial clusters.

To encourage ecosystem formation, policy makers have often focused—with mixed success (Lerner 2009)—on interventions designed to provide seed capital or attract venture capital to a region (e.g. tax breaks for early stage investment (Denes et al. 2023) or the formation of local government-backed funds). If innovation itself serves to draw capital to a region, however, policy makers have an alternative: focus on interventions designed to increase innovative activity and draw private investment to the region in its wake. Interventions designed to promote innovative activity may be more cost effective than creating a government-backed fund or offering subsidies to VCs to enter a region. If innovation attracts capital, such interventions may also be more likely to successfully ignite such a virtuous cycle, providing the investment opportunities that a capital intervention on its own does not supply. Identifying such innovation effects, however, is challenging.

To shed light on how innovation activity may attract investment capital, we take advantage of a shock to the production and accessibility of innovation in the vicinity of research universities: the Bayh Dole Act of 1980. Bayh Dole gave universities property rights to innovations developed at their institutions using federal research funding. The Act provided strong incentives for universities to engage in patenting and licensing activity. As a result, it led to the development of significant infrastructure for technology transfer which made university innovation become significantly more accessible to industry (Henderson, Jaffe, and Trajtenberg 1998; Sampat, Mowery, and Ziedonis 2003). Importantly, because universities differ in research strengths, the Bayh Dole Act provides a shock to innovative activity not only across geographic areas, but also, depending on the pre-Act research strengths of the nearby universities, across technologies within a geographic area. Our empirical approach uses this within-area variation in the industries related to university research strengths to measure the causal impact of the Bayh Dole innovation shock, while holding other geographic factors constant.

To build intuition for the strategy, consider the different pre-1980 innovative strengths of two strong research universities: the University of Texas at Austin (UT) and Johns Hopkins University (JHU). When Bayh Dole was passed, UT had a top electrical and computer engineering department. In contrast, JHU specialized in research in the biosciences. We can thus identify the specific industries in each geographic area that are most likely to benefit from Bayh Dole's shock to the accessibility of university innovation. In the Austin, TX area, we would expect the effects of Bayh Dole to be larger in local electronic and computer-related industries than in pharmaceutical or bioscience-related industries, while in Baltimore, MD, the area surrounding JHU, we would expect the reverse. The nature of this shock allows us to identify the effects of innovation on venture capital flows to regions, as we can hold a geographic area fixed, and identify effects off of cross-industry differences in VC flows, based on the intensity of field-specific innovation from the nearby university. Our analysis further tightens identification by saturating regressions with fixed effects, including controls for nationwide changes in the flow of VC dollars to particular industries such that our estimates cannot simply reflect sectoral trends.

Our empirical approach further takes advantage of a concurrent increase in fund flows to venture capital firms brought about by three policy changes. The first was the 1979 clarification to the Employee Retirement Income Security Act (ERISA) Prudent Man Rule, which allowed pension funds to invest in higher-risk assets. Quickly following it were the 1980 Small Business Act, which redefined VC fund managers as business development companies, and the 1980 ERISA Safe Harbor regulation, which sanctioned limited partnerships—the dominant organizational form in the VC industry. These regulatory changes resulted in large increases in committed capital to venture capital firms in the early 1980s—capital which then needed to be deployed across investment opportunities in the U.S. We provide evidence suggesting that these funds were disproportionately deployed in university areas and in the industries most related to their innovative output. And we test two leading alternative hypotheses reflecting the possibility that post-1980 VC allocations could be due to ERISA regulatory changes alone: (i) that the influx of VC funds was simply allocated much as pre-1979 VC funds were allocated, but on a larger scale and (ii) that these funds were simply deployed to areas with existing stocks of corporate innovation, which was much larger in scale and more geographically pervasive than university innovation (Figure 1).

In fact, the locations with the greatest VC growth from 1980 to 1990, shown in Figure 1 (Panel (d)), so closely resemble the locations of pre-1980 university innovation (Panel (b)) that the attraction of ex-post VC to ex-ante university innovation is apparent, visually, even before examining the full cross-industry variation in each location. We show empirically that the Bayh-Dole-induced shock to innovative activity in the vicinity of top research universities leads to the increased flow of VC funds to university regions over non-university regions, and, specifically, to the industries in each university region that are most closely related to the local universities' ex-ante technological strengths. We find an increase of $118,000 in VC funds after Bayh Dole per county-industry, per standard deviation increase in our university "innovation index" measure, or $54,000 per county-industry per citation to a university patent. This effect amounts to approximately $23.2 million additional VC investment per county after Bayh Dole, while the average university county saw a *total* increase of $61.1 million in VC funding over the 25 years surrounding both Bayh Dole and the regulatory changes that increased the supply of VC funding. Simply put, the Bayh Dole's shock to university innovation appears to account for more than one third of the increase in VC funding to these locations. In addition, our estimates of the elasticity of the effect of Bayh Dole shows that there was a 3.5% increase in the supply of venture capital per 1% increase in citation weighted patents. The university innovation effect on VC flows is magnified in university areas that received the most federal research funding before Bayh Dole, further supporting the role of the policy change in releasing innovative output that in turn draws private capital investment.

We note that while the coincident ERISA regulatory changes increased the funds available to venture capitalists for investment shortly before the Bayh Dole Act increased access to university innovation, an overall increase in VC availability cannot, on its own, explain the effect we measure. In the absence of Bayh Dole, these funds would have been expected to flow to the areas and industries in which VC already had a presence or to the areas and industries in which corporate innovation—which comprises the vast majority of U.S. patenting—was prevalent. What we observe, in contrast, is that VC investment flows overwhelmingly to the regions and industries in which university innovation was strongest, even controlling for the geographic and technological distribution of corporate innovation and pre-existing VC investment.

While we focus on measuring the effect of a plausibly exogenous shock to innovation from universities on VC investment in a region, this focus does not preclude the complementary direction of causality: VC also stimulates further innovation activity (Kortum and Lerner 2000). This second direction of causality is a necessary component of the "virtuous cycle" of innovation and capital exhibited by successful entrepreneurial clusters. We provide two new pieces of evidence on the effects of VC financing on future innovative activity, expanding on the patterns documented by Kortum and Lerner (2000). First, using the post 1979 increase in VC fund availability from ERISA as a shock to the overall supply of venture capital investment, which in turn should impact corporate innovation activity, we find that the pre-1979 distribution of VC investment across geographic areas and industries strongly predicts post-ERISA corporate innovation activity, but only to the extent that these ex-ante investment patterns are correlated with university innovative strengths.

Second, we find that, in addition to predicting VC disbursements, ex-ante (pre-1980) university innovation activity also predicts the areas and industries of post-Bayh-Dole corporate patenting, even controlling for prior corporate innovation activity. This finding is consistent with the ability of venture capitalists to find and fund the best *new* investment opportunities as they emerge. Using data from Guzman and Stern (2020) on business registrants and their eventual successful exit events, we show (i) that ex-ante university innovation is a strong predictor of subsequent high growth entrepreneurial entry across areas; and (ii) that controlling for contemporary VC investment nearly eliminates this effect—in other words, VCs identify precisely the high growth entrepreneurs launched by cutting edge university ideas. This new evidence illustrates the critical role played by both sides of the innovation-capital relationship and suggests a mechanism through which university innovation attracts VC: the entry of high growth entrepreneurs into university areas and industries related to those universities' research strengths.

Our findings offer a number of distinct contributions to the existing literature. Disentangling the complex two-way relationship between innovation and capital has long challenged scholars of entrepreneurial finance. This paper brings new identification using a national policy change that created an influx of innovation to industry, combined with cross-area and industry variation in the intensity of new, relevant technologies.

Second, we provide policy-relevant evidence suggesting that the encouragement of innovation activity can draw capital to a region seeking to develop an entrepreneurial cluster. Recognizing the strong link between entrepreneurial activity and economic growth (Jovanovic and MacDonald 1994; Davis and Haltiwanger 1992; Davis, Haltiwanger, and Schuh 1998; Haltiwanger, Jarmin, and Miranda 2013; Decker et al. 2014; Fairlie, Miranda, and Zolas 2019; Guzman and Stern 2020), policy makers often seek ways to stimulate and support entrepreneurial activity in their local areas (Lerner 2009). Entrepreneurs are often considered to be drivers of urban growth in general, and of innovation-driven growth in particular (Shane 2004; Glaeser and Kerr 2009; Agrawal, Cockburn, and Rosell 2010; Glaeser, Kerr, and Ponzetto 2010; Glaeser, Kerr, and Kerr 2015; Hausman 2020). Our findings suggest that one additional tool in the policy maker's toolbox is to engage in policies and interventions that encourage innovation activity, while allowing commercialization to be supported by private capital that then flows into the market in its wake.

Third, our paper contributes to a large literature on the sources of agglomeration economies that generate clusters of industrial activity and healthy entrepreneurial ecosystems. Knowledge spillovers, input-output relationships (supply chains), and labor pooling have long been thought to drive the co-location of firms (Marshall 1890; Ellison, Glaeser, and Kerr 2010; Greenstone, Hornbeck, and Moretti 2010). Substantial theoretical and empirical evidence supports the notion that innovation and entrepreneurship emerge in large part from the mixing of ideas in localities (Glaeser et al. 1992; Duranton and Puga 2001; Agrawal, Kapur, and McHale 2008) and that use of innovation is disproportionately local (Jaffe, Trajtenberg, and Henderson 1993; Kerr 2010). Our paper illustrates the importance of input-output relationships in facilitating innovative clusters around universities, as VC is a critical input for many entrepreneurs and is allocated disproportionately locally, likely due to the ease of monitoring and advising proximate companies (Lerner 1995; Chen et al. 2010).

Finally, our findings contribute to the growing literature on the influence of universities on economic growth. Universities may generate positive spillovers for their local economies via skilled workers (Moretti 2004; Cantoni and Yuchtman 2014), university spending (Kantor and Whalley 2014), or knowledge spillovers (Hausman 2022). Our paper demonstrates an additional mechanism through which universities generate clustered growth: by attracting venture capital to finance the university-related frontier innovation of local entrepreneurs.

The paper proceeds as follows. Section 2 describes the features of the Bayh Dole Act that make it a useful setting in which to study the relationship between innovation and capital. Section 3 describes the data used. Section 4 presents our empirical analyses and findings. Section 5 concludes.

2. THE BAYH DOLE ACT OF 1980

Until the 1980s, many American universities were reluctant to engage directly in commercialization of research. Typically, this avoidance was justified by arguments that patenting and licensing of technology removed knowledge from the public domain. Many universities feared that commercialization compromised the academy's commitment to open science, or that profit motives might undermine the purity of the scientific endeavor. Sampat (2006) describes Columbia University's reasoning that patenting activity "is not deemed within the sphere of the University's scholarly objectives." Many top research universities went so far as to explicitly forbid the patenting of biomedical research (Mowery and Sampat 2001).[1]

The legal regime further disincentivized commercialization of university research. Rights to intellectual property developed at universities using federally-funded research—which constituted the majority of total activity at U.S. universities—were held by the federal government.[2] While researchers could patent their innovations, they could not keep any royalties from licensing such patents unless they negotiated a special Institutional Patent Agreement (IPA) with the granting agency—a process typically involving lawyers, lengthy negotiations, drafts of agreements, and significant other administrative burden. While government title purported to promote a regime of "open science," in practice, most innovations in the public domain were not publicized or commercialized, and only 5% of the 28,000 patents owned by the federal government in 1976 were licensed.[3] Universities and innovators themselves—those most familiar with the technologies to be transferred—had little incentive to promote their ideas to industry.

[1] While some universities (primarily land-grant institutions that had always been more practically oriented and responsible to their local economies, see e.g., Goldin and Katz 2009) were involved in patenting on a smaller scale during this period, most kept their commercialization activities at arm's length in order to avoid direct association with the university. This commercialization activity was typically done either by contracting with the Research Corporation, an independent institution which administered patents of a number of universities, or by establishing a research foundation only loosely affiliated with the university.

[2] From 1972 to 1980, 66-69% of university research expenditures came from federal sources (Statistics calculated from the NSF Survey of Research and Development Expenditures at Universities and Colleges). These percentages represent averages across all universities and colleges surveyed; some institutions may have had even higher federal funding shares.

[3] Federal Committee on Science and Technology (FCST) Report, 1976.

The debate leading up to the passage of the Bayh Dole Act focused primarily on the benefits of public knowledge and "open science" versus the benefits of incentives to innovate and commercialize research. One view held that federally financed innovations should be kept in the public domain to maximize potential spillovers. Countering it were those worried that private enterprise would not fully invest in discovery and commercialization without stronger intellectual property protection that allowed them to benefit from the innovation developed in the course of contract R&D. Concerns regarding the U.S.'s ability to maintain economic competitiveness added further pressure to provide incentives for innovation.

In December 1980, Congress passed the Bayh-Dole Act. The Act standardized patent policy across granting agencies and reversed the presumption of federal title to inventions developed under federally funded research. The Bayh Dole Act gave universities the right to patent, own rights to, and keep royalty revenues from innovations developed using federal research funding. As quid pro quo, the Act also required universities to actively promote the inventions' commercialization, grant the federal government a non-exclusive license, and share any royalties with the inventor. In 1984, Congress further passed the Trademark Clarification Act, which removed restrictions on the types of inventions universities could own, and on the transfer of property rights to other parties. Taken together, these laws significantly strengthened the incentives of universities and faculty to produce, patent, and commercialize innovation.[4]

Universities and faculty appear to have responded to these new incentives, opening Technology Transfer Offices at increasing rates in the 1980s and early 1990s (Feldman et al. 2002).[5] Patenting from universities rose correspondingly (Henderson, Jaffe, and Trajtenberg 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 (Thursby, Jensen, and Thursby 2001). While only 55 universities had been granted a patent in 1976, 340 universities

[4] For the purposes of this paper, we refer to the Bayh-Dole Act as the law change driving identification of the empirical analysis. In practice, however, the two laws together comprised the change in the legal regime, as discussed in Hausman (2022). We consider December 1980 as the date of the change for the purpose of our empirical analysis.

[5] Certainly, the increased commercialization incentives may have incentivized researchers to alter the content of their research, in particular from more basic to more applied research. While both plausible and possible, this possibility does not interfere with either identification or interpretation of our results. If university research changes technological direction, then the pre-Bayh Dole and Trademark Classification Act measure of university strengths should not do a good job of predicting which local industries will be affected, and the effect measured should be attenuated to zero. If university research becomes more short-term focused or immediate, then one should expect to see effects diminish rapidly over time, which we do not observe. See e.g. Lazear (1997), Thursby and Kemp (2002), Thursby and Thursby (2007), Mowery and Ziedonis (2000), Mowery et al. (2001) for further discussion and case studies of these issues.

had been granted at least one patent by 2006.[6] Although it is difficult to say whether faculty responded by producing more innovation after Bayh-Dole, Lach and Schankerman (2008) provide evidence suggesting that faculty responded to stronger royalty incentives by producing higher quality innovation.[7]

Overall, the Bayh-Dole Act, with its effects on both university culture and incentives, resulted in a significant shift in the relationship between universities and industry. While prior to the Act, large scale technology and idea transfer from universities was nearly impossible to achieve, the Act strengthened property rights, standardized these rights across granting agencies, and provided significant economic incentives to both researchers and university administrations to engage in patenting and licensing activity.

3. DATA AND SAMPLE

3.1. NBER Patent Data

We use patent data for several purposes, including to measure (i) universities' pre-Bayh-Dole innovative strengths, (ii) corporate innovation outcomes, and (iii) the pre-Bayh-Dole distribution of corporate innovative activity across industries and areas as a counterfactual target for VC flows. 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, Jaffe, and Trajtenberg 2001).[8] The data contain year of patent application and grant, assignee, assignee location, patent technology class, and forward and backward citations. Assignees (patent owners) may be individuals, U.S. or foreign corporations, U.S. or foreign governments, hospitals, or universities. We use the subset of patents assigned to universities and university-affiliated hospitals to generate our sample of innovating universities, identify the research fields in which each university is highly innovative, and connect these research fields to the industries that may use a particular research field's innovations.[9]

[6] Counts calculated from NBER patent data.
[7] There 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 2004).
[8] The 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/patentdataproject/Home.
[9] The main sample includes the top 100 patenting universities and affiliated hospitals between 1976 and 2006, the entire period of the data. These 100 universities are located in 75 counties. A sample used in robustness tests includes

Additionally, we use data on the distribution of pre-1980 corporate patents to help distinguish the effects of Bayh Dole from that of the 1979 ERISA Prudent Man Rule, which may have increased VC funding to areas with strong corporate innovation.

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.

3.2. The Hausman (2022) Innovation Index

To construct a measure of university innovation and its relationship to specific industries, we follow Hausman (2022), and begin with patents produced by the universities and hospitals in our sample. 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 connect to a specific industry. We follow Kerr (2008) and use a probabilistic concordance constructed by experienced practitioners that weights each 3-digit SIC industry in terms of the probability it will use a patent given its technology classification.[10] The weights, w, 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 contain multiple universities, the index is then summed across universities. Figure A1 presents a stylized example of how to construct the index according to the following equation:

$$index_{ci} = \sum_{u \in c} \sum_{n} w_{in} p_{un}$$

where p is the number of citation-weighted patents granted to university u in technology class n, and w is the frequency of use weight for patent class n in industry i. The measure is then standardized to be mean zero, standard deviation one.

3.3. NSF Federal Research Funding to Universities

the top 200 patenting universities and affiliated hospitals (in 125 counties) during the same period. Patenting is highly concentrated among the top universities and hospitals and tapers off quickly for lower-ranked institutions.

[10] This concordance updates work done by Brian Silverman and was first developed in the early 1990s when the Canadian patent office assigned multiple classifications to each patent upon granting (Silverman 1999). 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.

Data on federal research funding to universities spanning the period 1963-2007 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 funding amounts by government agency, university campus, category of spending, and year. We use average annual funding amounts to the top universities in our sample in the five years leading up to Bayh-Dole, 1976-1980, to approximate the scale of ex-ante research explicitly subject to changes brought by Bayh-Dole, although in practice these changes affected most university research because of the infrastructure required for commercialization.

To provide a sense of the funding magnitudes, in 1980, MIT received $163.2 million in total funds, $26.9 million of which came from the Department of Defense (DOD) and $27.2 million of which came from the National Institutes of Health (NIH). A much less research-intensive university, Montana State University at Bozeman, received considerably fewer federal funds in 1980: $10.6 million total, of which $381,000 originated from DOD, and $346,000 originated from NIH. As with patenting activity, federal funding is highly concentrated among top universities.

3.4. University Counties

In our main sample, we consider counties containing top 100 universities to be "university counties;" the top 100 patenting universities reside in only 75 counties. University counties are considered to be "treated" by the innovation index and the federal funding associated with the local university.[11] In robustness work, we expand the definition of university county first to include adjacent counties and second to include those within 75 miles of the university. We also show robustness to expanding the definition to include the top 200 patenting universities (notably, the R1 classification for research universities included only 137 universities in 2022.)

3.5. VC Funding Data

Our VC data comes from Thompson VentureXpert at the deal level, with information on funded companies, location, industry, investor, and funds invested. We aggregate these deal level data to the county-SIC3-year level, computing three measures: Total Number of Active VC

[11] We provide support for this definition of treatment by providing evidence of geographic decay in the effects of the Bayh-Dole reform for counties further from universities. In our analysis, we re-estimate many of our main results with a sample that allows all counties adjacent to the university-containing county or within a 75-mile radius of the university's own county to be affected by the university. In the adjacent county analysis, we treat all counties containing a university or directly abutting a university county to be considered a "university county". In the 75-mile sample, all counties within a 75-mile radius are considered "university counties".

Investors (*Num Investors)*, Total Number of Deals conducted (*Num Deals*), and Total Funding Invested (*Total Funds)*.

3.6. Corporate Innovation Index

We measure the pre-Bayh-Dole distribution of corporate innovation across geographic areas and industries much as we do for university innovation, using patents produced in the years 1976-1980. The corporate innovation index for each county *c* and industry *i* is the weighted sum over technology classes *n* of citation-weighted corporate patents, *cp*, in county *c* and technology class n, where the frequency of use weights *w* reflect the probability that a patent of each technology class n is used in industry *i*:

$$corpindex_{ci} = \sum_{n} w_{in} cp_{cn}$$

As with the university innovation index, the corporate innovation index is standardized to be mean zero, standard deviation one, such that the coefficients are directly comparable.

3.7. VC Index

To estimate a plausibly causal effect of VC in certain analyses, we would ideally like to measure the presence of venture capital across geographic areas and industries in a manner that is exogenous to corporate innovation. Measuring pre-ERISA (pre-1979) VC allocations is a first step, since ERISA greatly increased the scale of funds available to VC firms for investment and thus provides useful variation over time. But of course, even before ERISA, VC investments were presumably made where opportunities for useful innovation were greatest – likely where corporate innovation was strong. Because corporate innovation exhibits high autocorrelation over time, measuring ex-ante VC on its own would be endogenous to ex-post corporate innovation. We thus follow Kortum and Lerner (2000) in scaling ex-ante VC in each county and industry by corporate R&D investments in the same locations. By using investment inputs rather than patenting outputs, we aim to control for expected innovation opportunities, given information available at the time.

We measure the VC index in county *c* and industry *i* as the VC funds invested in that county and industry in the years 1970-1979 divided by county-industry level corporate R&D investment (from Compustat) in the same years:

$$VCindex_{ci} = \frac{VC_{ci}}{RnD_{ci}}$$

We standardize our index to be mean zero and standard deviation one, as with the other indices, and we refer to it as the *Ex-Ante VC Index*.[12] The ability of this measure to predict post-1979 corporate innovation will thus reflect venture capitalists' ability to identify and invest in the places and industries that would become the strongest in *frontier innovation*, i.e. as distinct from the areas strongest in *established innovation* as of 1979.

3.8. High Growth Entrepreneurship Measures

To measure high growth entrepreneurship activity by county, we use data provided in 2020 by the Startup Cartography Project (SCP), described in detail in Guzman and Stern (2020). These data are categorized by the business registration year of new firms and offer information on these registrants' eventual business outcomes. We use four variables calculated by the data providers: *Entrants with Eventual Growth Events*, *Quality-Adjusted Quantity of Entrants*, *Entrant Quality Index*, and *Realized-to-Expected Eventual Growth Events*.

3.9. Final Sample

The sample that results from combining these various data sources contains observations at the county-industry-year level, where industries are measured at the 3-digit SIC code level and the sample years are 1970-1995. Because there are often multiple universities and hospitals in a given county or in nearby counties, their associated treatments (federal funding and the Innovation Index) are summed across universities within treated county-industries. Thus, for example, Middlesex County, MA, is treated by both Harvard and MIT, and a biomedical industry in that county would be treated by the biomedical innovation index that is the sum of those from each school. We assume Bayh-Dole treats only university counties and only in the years after 1980.

Table 1, Panel A presents descriptive statistics for the estimation sample at the county-industry-year level. To provide a sense of the state of university counties before the policy changes we study, Panel B presents county-level statistics for university counties prior to 1979. Panel C describes the growth in VC experienced by university counties over the sample period.

[12] Our results are robust to an alternative construction of the Ex-Ante VC index constructed using investor counts rather than invested dollars.

4. EMPIRICAL ANALYSIS

To measure the ability of local innovation activity to attract private capital flows from venture capitalists, we would ideally like to allocate innovation randomly to otherwise similar locations and measure venture capital investment in those locations after the innovation is endowed, relative to before. In reality, of course, innovation is not exogenously endowed or allocated. Instead, we take advantage of a national policy change–the Bayh Dole Act of 1980–that generates a plausibly exogenous shock to the spread of innovation from universities and should have different expected effects across geographical areas and industries.

4.1. Main Results

To set the stage, we begin with a basic, relatively weakly-identified, comparison of university counties to non-university counties before and after the passage of Bayh Dole, before turning to our main analysis, which accounts for the differential impact of universities on industries in their region most tied to their innovative activities. If innovation serves to attract private investment capital from VCs to a region, we would expect the differential between university counties and non-university counties to be larger after the passage of Bayh Dole, which provides a shock to the innovative output in university counties. Figure 3 presents the raw averages of VC dollars invested, number of unique active VC investors, and number of VC deals over time for university and non-university counties. As can be seen clearly from the figure, university counties experience a larger increase in all three VC activity variables after 1980, relative to non-university counties. The graphs for the three VC measures show similar pre-treatment trends in university and non-university counties, consistent with VC funding flowing to areas that are "shocked" with more innovation. To examine this cross-county relationship more formally, we estimate variations of the model:

$$(1)\ y_{cit} = \beta_0 + \beta_1\left(I^{year>1980} * I_c^{univ\_county}\right) + \vartheta_{it} + \theta_{ci} + \epsilon_{cit},$$

where the unit of observation is a county-industry-year; the coefficient β_1 captures the differential effect of the Bayh-Dole Act on university-containing versus non-university-containing counties, after relative to before the passage of the law; ϑ_{cit} are industry X year fixed effects; and θ_{ci} are county X industry fixed effects. The inclusion of industry X year fixed effects is meant to capture industry increases in venture capital nationwide that are not attributable to university innovation, while county X industry fixed effects account for location-specific industry strengths that are consistent over time. Due to the fixed-effects structure, both lower order terms—the indicator for university-containing county and the indicator for year post 1980—are absorbed in the fixed effects. Standard errors are clustered at the county level. y_{cit} are various venture-related and corporate innovation outcome measures.

The estimates are presented in Table 2. The outcomes measures are our three measures of VC activity: (1) total VC investment dollars deployed in the county-industry-year (measured in $ million); (2) the number of VC deals in the county-industry-year; and (3) the number of unique active VC investors in the county-industry-year. Columns (1)-(3) define a university county as a county that contains a university, while columns (4)-(6) define a university county as a county that either contains a university or is adjacent to a county that contains a university. In all six columns, across all three measures of VC activity, we observe the same basic pattern. In all models, the measures of VC activity larger post Bayh-Dole in university counties relative to non-university counties. When compared to the summary statistics for pre-1979 levels of VC activity in university counties shown in Table 1, the coefficient in column (1) represents a 51.5% increase the amount of yearly VC investment in university counties from a base of $0.96 million, the coefficient in column (2) corresponds to an increase of 17% in the number of deals from a baseline of 1.02, the coefficient in column (3) corresponds to an 18% increase in the number of investors from a base of 1.79. As expected, the magnitude of the coefficients is lower when university counties are defined as those either containing a university or adjacent to a university-containing county (Columns (4)-(6)). Importantly, these cross-county results reflect average effects across many university county-industries, most of which do not attract VC at all, and, as a result, their magnitudes may mask larger industry-specific effects in industries closely tied to university innovation output, as we will see in a moment.

While these patterns are consistent with the notion that the Bayh Dole shock to accessibility of university innovation leads to greater flows of private capital into university counties, these tests are relatively weakly identified—university and non-university counties differ on a variety of dimensions that could affect VC outcomes. To fully identify the effects of the Bayh Dole Act's innovation shock on VC funding flows, we next take advantage of cross-sectional variation in the industries in each county most likely to be affected by such a shock, given the pre-treatment research expertise of the nearby university, as measured by the Hausman (2022) *Innovation Index*.

The expected differential effects of the shock on VC funding deployed in each county-industry are best illustrated by example: at the time of Bayh Dole's passing, University of Montana, Bozeman, for example, was particularly strong in research in optics and photonics—it has a high innovation index in that industry—and we thus expect to see VC funds flow specifically to that industry in the Bozeman area in the wake of the Act's passage. Similarly, Texas A&M University was particularly strong in innovation in chemical engineering closely related to biotechnology, and we expect more VC fund flows to investments into biotechnology in the College Station area.

Formally, we estimate variations on the following equation:

$$(2)\ VC_{cit} = \beta_0 + \beta_1(I^{year>1980} * univ\_index_{ci}) + \vartheta_{it} + \varphi_{ct} + \theta_{ci} + \epsilon_{cit},$$

where the unit of observation is a county-industry-year; the coefficient β_1 captures the differential effect of the shock to university innovation on high innovation index versus low innovation index industries in a given region following the passage of the Bayh Dole Act, relative to before the passage of the law; ϑ_{cit} are industry X year fixed effects; φ_{ct} are county X year fixed effects; and θ_{ci} are county X industry fixed effects. The inclusion of industry X year fixed effects captures rising VC flows to each industry nationwide, while the county X year fixed effects absorb any cross-industry shocks over time in a given location that are unrelated to university innovation. County X industry fixed effects account for location-specific industry strengths that are consistent over time. Lastly, $univ\_index_{ci}$ is the standardized Hausman (2022) university innovation index for county *c* in industry *i,* reflecting the extent to which each industry in each location should be affected by the innovation shock, based on the strength of its relationship to the innovation output of the specific universities in that county. Due to the model's saturation with fixed effects, the main effect of the innovation index is absorbed, as is the indicator for post-1980. Standard errors are clustered at the county level.

Table 3 Panel A presents the results of estimation of equation (2), where the outcome variables of interest are the total VC dollars invested in a county-industry-year in columns (1) and (2), the number of unique active VC investors in the county-industry in columns (3) and (4), and the number of VC deals in the county-industry in columns (5) and (6). In columns (1), (3), and (5), we use a version of the innovation index that has been standardized to mean 0 and standard deviation 1, such that the magnitudes of β_1 can be interpreted in terms of the effect of a one standard deviation increase in innovation at the county-industry level. In columns (2), (4), and (6), we estimate the models using a non-standardized version of the innovation index, such that the coefficient measures the effect associated with an additional citation-weighted patent in that industry-county. The coefficient of interest, β_1, is positive and statistically significant across all four models. Looking first at the estimates in columns (1), (3) and (5), the coefficient estimate in column (1) suggests that a one standard deviation increase in the innovation index led to a $118K increase in VC funding deployed in the county-industry after Bayh-Dole, representing a 101% increase in university-county venture capital investment from the pre-Bayh-Dole baseline. The coefficient in column (3) represents an increase of 40% in unique local investors off the 1970 base of 1.79 investors per university county. Meanwhile, the coefficient in column (5), multiplied by the average number of industries per county with VC deals, represents a 30% increase in deals off the 1970 base of 1.02 deals per university county, per standard deviation increase in the innovation index.

Looking at columns (2), (4), and (6), we estimate the impact of an additional citation-weighted patent issued to a university. The coefficient in column (2) shows that each new citation-weighted patent corresponds to an increase of $54 thousand in venture capital, a 45% increase from the pre-Bayh-Dole baseline. The coefficient in column (4) shows a 18% increase in the number of investors in university counties from the pre-Bayh-Dole baseline and the coefficient in column (6) shows a 13% increase in the number of deals from the pre-Bayh-Dole baseline. In appendix Table A1, we show that our results for the amount of venture capital invested the number of investments and unique investors are robust to log-transformation and inverse-hyperbolic-sine transformation of the dependent variables.

From an identification standpoint, estimation of Equation (2) assumes that more and less treated county-industries were on similar VC activity growth trajectories before the innovation shock occurred in 1980 with the passage of the Bayh Dole Act. To test that assumption, Figure 4 first presents event study figures in which points represent treatment effects in each year from 1970 to 1990; for each of the VC outcome variables, the treatment effects are statistically indistinguishable from zero before 1980, demonstrating that the parallel trends assumption holds. The assumption that the industries and locations we identify as receiving the largest boost in VC allocations after Bayh Dole were not already on faster growth trajectories for VC funding before the Act for reasons other than university research is further supported by empirical patterns documented in Hausman (2022) that suggest that university-related industries and areas did not grow differentially before the law passage than non-related and non-university areas, nor did corporate patenting in the relevant counties and technologies.

We perform a number of additional analyses to assess the robustness of our findings in Panel A. First, our main results use a window between 1970-1995, so we examine the robustness of our results to a shorter window from 1975-1990 in appendix Table A1. We find that the results are not substantially changed when considering a shorter time window. Next, our main results utilize a sample of the top 100 innovating universities. We find that the results are nearly identical if we expand our sample to include the top 200 most innovating universities (Appendix Table A2). In appendix Table A3, we examine the robustness of our university innovation index by including patents through 1985 in our measure of university innovation intensity across industries, increasing the number of patents which define the university's expertise while introducing post-Bayh-Dole endogeneity, and find nearly identical results as presented in Table 3, affirming the quality of our measure of university innovation.

In Panel B, we use a logarithmic transform to provide elasticity estimates of the effect of Bayh-Dole on venture capital investment dollars (1), unique investors (2), and number of deals (3). In each of these models, we transform the dependent variable and the innovation index using the standard log(1+x). An increase in 1% in the innovation index for a single industry in the county yields a 2.6 to 3.5% increase in investment dollars, investors, and deals. Altogether, the estimates suggest a substantial impact of the supply of new innovation on the allocation of early-stage investment. Our results are unchanged in magnitude, direction, or statistical significance when we use the inverse hyperbolic sine transformation on our three measures of VC activity.[13] Similar to the robustness tests described above, we show little change in our results to changes in time window (Table A1), in the sample of universities (Table A2) or construction of the university innovation index (Table A3). In appendix Table A5, we additionally show that our results, while smaller in magnitude, are robust to the exclusion of the top ten universities in pre-Bayh-Dole patenting intensity and additionally excluding California and Massachusetts, the two highest regions in venture capital allocation in the pre-Bayh-Dole period.

4.2. Geographic Decay

[13] We chose the log-log specification in our main results rather than an alternative specification with inverse-hyperbolic-sine transformation, because the results of that transformation are not immediately interpretable as elasticities in our data because our dependent variables range too close to zero (Bellemare and Wichman 2019).

Our main results assume the university "treats" only the county in which it is contained. Next, we explore the geographic decay of knowledge spillovers and the corresponding local nature of effects. Because knowledge spillovers are disproportionately local in nature (Henderson et al, 1994), we would expect our results to decay with distance. We re-run our analyses with two alternative datasets: one in which we code counties adjacent to university counties as treated and one in which we count as treated all counties within 75 miles of a sample research university. The estimates are as expected: the effect of Bayh-Dole is smaller as we get further from the university (Appendix Table A4). The fact that these estimates decay with distance further supports the importance of local knowledge spillovers—as university-related corporate innovation and entrepreneurship increase more in close proximity to the university—and of localized input-output relationships, as VC flows disproportionately to firms in the university's immediate vicinity. In the absence of disproportionately local knowledge spillovers, university innovation would not draw VC funding to the local area—innovation could spillover to any region, however far away, and VC investment would follow that knowledge spillover. Our estimates in Appendix Table A4 thus further affirm the important role of local knowledge spillovers in determining where commercialization of innovative activity occurs.

4.3. Mechanism Test: Federal Funding

Because Bayh Dole technically affected university innovation produced in the course of federally funded research, universities that received the most federal research funding before the law was passed would have had the most research suddenly opened to commercialization. We can thus provide further support for our identification scheme and mechanism of effects by employing variation in the amount of federal research funding received by universities in the years prior to Bayh-Dole. If federal research funding increases the intensity of treatment, then the VC growth gap between more and less treated industries (as measured by the innovation index) should be *greater* in counties that received more federal research funding ex-ante. This prediction amounts to estimating an equation analogous to equation (2), but in which the term of interest is now a triple interaction between the innovation index, an indicator for years after Bayh Dole, and average annual federal funding to universities in the county in the years leading up to 1980:

$$(3)\ VC_{cit} = \beta_0 + \beta_1(I^{year>1980} * univ\_index_{ci}) + \beta_2(avg\_Fed\_Fund * I^{year>1980} * univ\_index_{ci}) * + \vartheta_{it} + \varphi_{ct} + \theta_{ci} + \epsilon_{cit}.$$

β_2 is expected to be positive if federal funding magnifies between-industry differences in effects of university innovation. The unit of observation is a county-industry-year, and the coefficient β_1, as before, captures the differential effect of the shock to the spread of university innovation on high innovation index versus low innovation index industries in a given region following the passage of the Bayh Dole Act, relative to before the passage of the law. The fixed effects are identical to those in equation (2): ϑ_{cit} are industry X year fixed effects; φ_{ct} are county X year fixed effects; and θ_{ci} are county X industry fixed effects. $univ\_index_{ci}$ is the standardized Hausman (2022) university innovation index for county c in industry i. Due to the fixed effects structure, the innovation index and federal funding main effects are absorbed, as is the indicator for post-1980. Standard errors are clustered at the county level.

Table 4 presents estimates of this model for our three VC activity variables. The estimates support the notion that newly commercialized federally funded university innovation is the driver behind increased VC investment activity in the university areas post-Bayh-Dole. In all three specifications, β_2 is positive and strongly statistically significant, indicating that higher federal funding in the pre-period magnifies the university innovation effect documented in the previous tables.

4.4. Heterogeneity in the Treatment Effect by County Characteristics

In addition to levels of university-level federal funding, which tie directly to the mechanism for the impact of Bayh-Dole implied by our design, counties can vary substantially in ways that are likely to impact the likelihood of commercialization of intellectual property derived from government sponsored research, and, as a result, the impact of the Bayh-Dole Act. We explore treatment effect heterogeneity in Table 5. For each of the models in the table, we create a triple interaction term where we take our post-treatment indicator X innovation index and then interact that with an indicator variable for whether that county is above or below the median nationally for a variety of county characteristics.[14] Specifically, we measure above/below median in household

[14] All county-level data were taken from either the 1980 census data accessed via NHGIS or the County Business Patterns data (CBP).

income (column 1), share of adults with at least a BA degree (column 2), county population (column 3), share of population in urban living (column 4), level of corporate patenting (column 5), employment level (column 6), average wage per worker (column 7), and average establishment size (column 8). We utilize total VC dollars invested in the county-industry as our VC activity outcome variable.

Consistently across all models in Table 5, we observe positive and statistically significant estimates for the triple interaction term. Moreover, in nearly all models (the exception being the estimates in column (6) for treatment heterogeneity across employment levels), while the triple interaction term is significant, the original interaction term (post Bayh-Dole X Innovation index) loses statistical significance. Put differently, the estimates suggest, perhaps unsurprisingly, that the effects of Bayh-Dole's shock to university innovative output are concentrated in counties with above median income, population, university education, urbanization, corporate patenting, wages and establishment size. While Bayh-Dole increased access to university innovative output available for commercialization activity, not all regions have the capacity to utilize this research output to commercialize and create VC-backed companies.

4.5. University Innovation Shock (Bayh Dole)? Or VC Availability Shock (ERISA)?

The passage of Bayh Dole coincided with other regulatory changes that affected the amount of capital available for VCs to invest more generally. In particular, the Employee Retirement Income Security Act (ERISA)'s 1979 clarification of the "Prudent Man" rule in late 1979 allowed pension funds to invest in higher-risk asset classes. This rule change allowed funds from defined benefit pension funds to be funneled into the VC industry, as a result of which VCs suddenly had considerably more capital available to deploy than they had in prior years. A concern is that the increase in funding to university counties and related industries after 1980 we show above is simply due to this general increase in VC funding, and not specifically due to the fact that the universities now had more innovative output available for commercialization. While the geographic and industry correlation with local university strengths as well as the evidence on the federal research funding mechanism lend strong support to the university innovation shock hypothesis, the 1979 ERISA change was extremely significant for the growth of the VC industry, and worthy of direct consideration. We thus turn next to exploration of alternative hypotheses as to where such new VC funds would have been invested in the absence of a university innovation shock.

An obvious first concern is that increased VC funding post ERISA simply flowed to industries and counties where it had previously been present, and that our analysis is picking up this persistence in locations and industries with no connection to the increase in university innovative output associated with the Bayh Dole Act. Presumably, if the effects we document are simply the result of increased VC funding flowing to the same locations it was before, we should see this increase in funding occur across the board in counties that previously had VC activity, and not just in university counties. While the estimates in Table 2 and 3 suggest that VC investment post 1980 increases disproportionately in university counties, our first alternative hypothesis is thus that the increase in "dry powder" for VC investment post-1980 simply flows to locales and industries in which VCs were already investing pre-1980, and that these happen to disproportionately include university counties and industries related to their research strengths—despite the fact that before the Bayh Dole Act was passed in 1980, universities lacked incentives to commercialize their research. To test this alternative story, we construct an index measure for pre-1979 VC activity. We follow Kortum and Lerner (2000), and scale VC investment by contemporary corporate R&D expenditures (to control for known innovation opportunities). Our index is calculated at the industry-county level.

We then estimate the model:

$$(4)\ VC_{\ cit} = \beta_0 + \beta_1(I^{year>1980} * univ\_index_{ci}) + \beta_2(I^{year>1979} * VC\_index_{ci}) + \vartheta_{it} + \varphi_{ct} + \theta_{ci} + \epsilon_{cit},$$

where the unit of observation is a county-industry-year; the coefficient β_1 captures the differential effect of the shock to university innovation on high innovation index versus low innovation index industries in a given region following the passage of the Bayh Dole Act, relative to before the passage of the law; the coefficient β_2 captures the differential between high pre-1980 VC investment areas versus low VC investment areas pre-1980. Once again, ϑ_{cit} are industry X year fixed effects; φ_{ct} are county X year fixed effects; θ_{ci} are county X industry fixed effects; $univ\_index_{ci}$ is the standardized Hausman (2022) university innovation index for the county-industry; VC_index_{ci} is the county-industry specific pre-ERISA VC index, also standardized so that the coefficient is directly comparable to those on the other indices. Due to the fixed effects structure, all lower order terms are absorbed. Standard errors are again clustered at the county level.

Columns (1)-(3) of Table 6 presents estimates from models using our customary set of VC activity outcome variables. Across three VC activity variables, our estimates of β_1, our variable of interest, are positive and statistically significant, showing that increased supply of innovations had a marked impact on the allocation of VC to university counties in the industries most closely tied to the university's innovation output even after accounting for the scaled level of VC allocation before the reforms. In one out of the three models we observe a small and weakly significant association of post 1980 VC activity with pre-ERISA levels of VC allocation, unsurprising given the extreme geographic localization of venture capital (Chen et al. 2010). The magnitude of this coefficient, however, is between 5.3 times lower than the size of estimate of the effect of the university innovation index (coefficients are comparable given the standardization of the index variables). Indeed, across all regressions, the difference between these coefficients is statistically significant. The estimates suggest that the university innovation shock from Bayh-Dole leads specifically to disproportionate flow of VC investment activities to the affected industries in university counties even after accounting for pre-existing patterns of VC allocation pre-ERISA, supporting the causal channel for the impact of university innovation output on VC flows.

We provide a graphical illustration of the comparative impact of university innovation versus ex ante VC investment in Panel A of Figure 5. The points on the dark curve in the figure represent coefficients on university innovation index X year indicators in a fully expanded version of Equation (4), while the grey curves represent coefficients for ex ante VC index X year indicators.[15] Comparison of the two curves reflects the differences in treatment effects of ex-ante university innovation on VC outcomes versus that of ex ante VC allocation. Panel A demonstrates that VC funding after Bayh Dole (1980) flows specifically to industries in university counties that most correspond to the local university's research strengths, while we observe only limited and non-statistically significant increases in VC funding in county-industries with high ex ante VC allocation. In other words, the pattern observed in the data closely matches that which we would expect if Bayh Dole's shock to the incentives of universities to transfer technology into the commercial market in fact created innovation output that attracts subsequent VC funding, rather than being an artifact of the increased funding available post-ERISA. The estimates show little

[15] Note that both plotted curves are estimated by regressions that control for the other index. Thus, the university innovation effect on VC is the one estimated when controlling for the ex-ante distribution of VC investment.

support for the competing story that overall increased VC funding availability simply led to increased flows into counties with high levels of prior VC investment.

Of course, university counties may be highly innovative areas more generally. A second alternative to the university innovation shock hypothesis could be that university counties and their related industries simply had disproportionate shares of pre-1980 *corporate* innovation output, and that this corporate innovation activity is what drew VC dollars when they became available due to ERISA. Importantly, the maps in Figure 1 suggest that the geographic distribution of corporate innovation prior to 1980 was considerably wider than that of university innovation (Panels (a) and (b)). The industry distribution of established corporate innovation may also have differed somewhat from the distribution of industries affected by university innovation.

To formally test this second alternative hypothesis, we calculate an index measure for ex-ante corporate innovation by county and industry that is analogous to the university innovation index but is based on pre-1980 corporate patents. We then horserace the corporate and university innovation indices in the same regression, asking which type of innovation better predicts differential VC outcomes after 1980.

Formally, we estimate the following model:

$$(5)\ VC_{cit} = \beta_0 + \beta_1(I^{year>1980} * univ\_index_{ci}) + \beta_2(I^{year>1980} * corp\_index_{ci}) + \vartheta_{it} + \varphi_{ct} + \theta_{ci} + \epsilon_{cit},$$

where the unit of observation is a county-industry-year; the coefficient β_1 captures the differential effect of the university innovation shock on high innovation index versus low innovation index industries in a given region following the passage of the Bayh Dole Act, relative to before the passage of the law; the coefficient β_2 captures the differential effect on high corporate innovation index versus low corporate innovation index industries in a given county post 1980. Our fixed effects structure remains unchanged from the specification described in equation (4).

The results of the estimation are presented in columns (4)-(6) of Table 6. Similar to columns (1)-(3), we observe a positive and statistically significant coefficient on the university innovation index for all three measures of VC activity, controlling for the corporate innovation index interaction. Put differently, even controlling for the effects of the geographic distribution of pre-ERISA corporate innovation output, VC activity increases post-ERISA precisely where the predicted effects of Bayh Dole would expect it to be – in university counties, in the industries most closely tied to university innovation output. In contrast, we the coefficient on the corporate innovation index interaction does not load significantly in any of the specifications. These patterns lend further support for our interpretation of the Bayh-Dole reform as the major channel for determining venture capital allocation in this period, rather than ERISA.

In Panel B of Figure 5, we provide a graphical comparison of the impact university innovation to corporate innovation on subsequent VC investment. The graph is constructed using the same method as described above for Panel A of Figure 5, but using equation (5) instead of (4). Similar to the results in Panel A, we observe strong effects of Bayh-Dole in industry-counties with high levels of university innovation, and only limited and non-statistically significant increases in VC funding in county-industries with high ex ante corporate innovation. The pattern shown in Panel B of Figure 5 further supports our hypothesized effect of Bayh-Dole on the commercialization of university intellectual property, and provides little support for the competing story that VC dollars post-ERISA simply flowed to counties with high levels of ex ante corporate innovation.

Lastly, we concurrently explore the "dry powder" hypothesis and the corporate innovation hypothesis, horseracing both with our university index to further augment our individual channel tests above. We estimate variations on the following model:

$$\text{(6) } VC_{cit} = \beta_0 + \beta_1(I^{year>1980} * univ\_index_{ci}) + \beta_2(I^{year>1980} * corp\_index_{ci}) + \beta_3(I^{year>1979} * VC\_index_{ci}) + \vartheta_{it} + \varphi_{ct} + \theta_{ci} + \epsilon_{cit},$$

where the unit of observation is a county-industry-year; the coefficient β_1 captures the differential effect of the shock to university innovation on high innovation index versus low innovation index industries in a given region following the passage of the Bayh Dole Act, relative to before the passage of the law; the coefficient β_2 captures the differential effect of high corporate innovation index versus low corporate innovation index industries in a given county post 1980; and the coefficient β_3 captures the differential between high pre-1980 VC investment areas versus low VC investment areas pre-1980. Our fixed effects structure remain unchanged from the specification described in equation (4).

The results are presented in columns (7)-(8) of Table 6. Overall, the simultaneous estimates of the coefficients β_1, β_2, and β_3 show little difference from their separate estimates in Panels A and B. We observe a positive and statistically significant coefficient on the university innovation index in the post-Bayh-Dole period across our three different measures of venture capital allocation. Neither pre-Bayh Dole/ERISA VC activity nor pre-Bayh Dole/ERISA corporate innovation output exhibit a consistently significant relationship with post-Bayh Dole/ERISA VC activity in the county-industry.

4.6. The "Virtuous Cycle:" Innovation-Capital-Innovation

While we focus on measuring the effect of a plausibly exogenous shock to innovation from universities on VC investment in a region, the capital provided by VCs should also stimulate further innovative activity as shown at the national level by Kortum and Lerner (2000). Both directions of causality are necessary components of the "virtuous cycle" of innovation and capital that successful entrepreneurial clusters have, and other places lack. We next turn to providing additional evidence on this second direction of causality. We estimate models similar to those described in Equation (6), but we replace the VC outcomes on the left-hand side with corporate citation-weighted patenting outcomes, allowing us to shed further light on how pre-ERISA allocations of VC and corporate innovation activity across geographic areas and industries predict the county-industries of post-ERISA corporate innovation.

Table 7 presents the results of our estimation using the citation-weighted number of corporate patents. When the Ex-Ante VC Index is included alone in column (2), pre-Bayh-Dole VC investment does indeed predict corporate innovation, as in Kortum and Lerner (2000). When we add the university and corporate innovation indices to the regression in column (4), however, the university index remains positive and significant, while the coefficients on the VC indices become indistinguishable from zero. The estimates illustrate the virtuous cycle that exists between innovation and investment capital flows. A shock to university innovation draws VC funding and investors, who in turn fund further innovative activity, as shown by Kortum and Lerner (2000). Kickstarting the cycle, however, is the shock to university innovation and associated local innovative output, which serves to draw increased capital flows from the ERISA changes to the region. Once we control for both the existing stock of corporate innovation and the shock to university innovation output, VC dollars on their own do not exhibit a significant relationship with future innovation. Put differently, without innovation activity to provide opportunities for investment of funds, VC availability in a region (through a government fund, for example) may not be enough to drive future innovation activity.

These findings have significant implications for policy-making, suggesting that public efforts to kickstart innovation ecosystems may be better focused on supporting local innovative activity, even at the basic research level, than on merely creating investment funds or spending on matching or fund-of-fund schemes to try and draw outside VCs to the region. Notably, this "virtuous cycle" pattern, in which innovation attracts VC funding that in turn funds future innovation activity, may provide some explanation as to why many public programs to launch VC industries have not succeeded in jumpstarting innovation ecosystems as their government designers had intended (Lerner 2009).

4.7. Long Term Outcomes: High Growth Entrepreneurship

In our final analysis, we provide additional evidence suggestive of this virtuous cycle. To do so, we look specifically at high growth entrepreneurship outcomes, which are likely to be particularly affected by VC. While VC investments in an area may ultimately be reflected in future general corporate innovation, these investments should be even more closely tied to the frontier innovation of new and young firms.

We begin by examining the association between university counties, federal research funding, and high growth entrepreneurial activity. We estimate OLS regressions in which the dependent variable is one of four measures of innovation-driven entrepreneurship (IDE) obtained from the Startup Cartography Project (SCP) for the years 1988 to 1995, measured at the county-year level. The four outcome measures are: (i) the number of entrants with eventual growth events; (ii) the quality-adjusted quantity of entrepreneurial entrants; (iii) the entrepreneurial quality index (EQI); and the ratio of realized to expected eventual growth events. Panel A of Table 8 estimates models of the form:

$$(6)\ IDE_{ct} = \beta_0 + \beta_1 I_c^{univ\_county} + \vartheta_t + \epsilon_{ct},$$

while Panel B estimates models of the form:

$$(7)\ IDE_{ct} = \beta_0 + \beta_1 avg\_Fed\_Fund_c + \vartheta_t + \epsilon_{ct},$$

As in prior models, $avg\_Fed\_Fund_c$ is measured in the pre-Bayh-Dole period. ϑ_t are year fixed effects, and standard errors are clustered at the county level.

The estimates in Table 8 paint a consistent picture across models. University counties and those with higher pre-Bayh Dole federal research funding both have strongly higher levels of eventual high growth entrepreneurial entry. More specifically, for all four measures of entrepreneurship, for both the university county indicator and the average federal funding measure, we observe a positive and significant coefficient. The coefficient in Panel A, column (1), for example, suggests an increase of nearly three entrants with eventual growth events per year in university relative to non-university counties. The implication is that the raw difference in entrepreneurial entrants is much larger. While these estimates represent correlations, and are not identified, they are suggestive of better entrepreneurship outcomes near universities—especially near universities with high pre-existing levels of federal funding—after passage of Bayh Dole. Similarly, Panel B shows that the level of federal research funding allocated to the universities in the county has a large and statistically significant effect on the likelihood of observing growth events in university counties relative to non-university counties. For example, the coefficient estimate in column (1) suggests that an additional twenty million dollars in federal R&D funding is associated with one additional growth event per year.

To understand the extent to which high growth entrepreneurship emerges in locations with strong university innovation versus corporate innovation or VC investment, we return to our pre-pre-Bayh Dole index measures, aggregating them from county-industry level to the county level (SCP measures activity at the county level, without distinguishing by industry). Columns (1) and (4) of Table 9 indicate a strong positive correlation between pre-Bayh Dole university innovation and subsequent high growth entrepreneurship in the local area; the coefficient of 0.733 in column (1) suggests an increase of almost one entrant per year with an eventual growth event, per standard deviation increase in the innovation index. This correlation with university innovation barely declines when we control for the geographical distribution of established corporate innovation in columns (2) and (5), and the difference is not statistically significant (0.733 (0.270) declines to 0.651 (0.262), in column (2)). In other words, high growth entrepreneurship is correlated much more with the locations of university innovation than it is with corporate innovation.

To understand whether VC—which we now know is attracted to high university innovation areas—in turn stimulates local high growth entrepreneurs, we add a measure of *contemporary* VC investment to the regressions in columns (3) and (6) of Table 9. When this measure is included, we observe that contemporary VC dollars invested are not only strongly positively correlated with high growth entrepreneurship, but also drive down the coefficient on university innovation. The university innovation effect declines from 0.733 in column (1) to 0.220 in column (3), and from positive and significant in column (4) to zero in column (6). This result could not occur without a strong positive correlation between university innovation and *subsequent* VC disbursements. The implication is that university innovation stimulates high growth entrepreneurship predominantly through its attraction of VC investment. Put differently, VC investors are drawn specifically to the frontier innovation stimulated by basic university research, and they manage to identify precisely the entrepreneurial entrants most likely to succeed (or who can be led to success). Logically, VC is even more strongly correlated with the subset of corporate innovation that occurs in new, high growth firms. These results are consistent with the overarching hypothesis that a shock to innovative activity ignites a virtuous cycle, attracting capital that further stimulates innovation, and leading to the emergence of high growth entrepreneurial clusters.

5. CONCLUSION

Economists since Adam Smith have emphasized the importance of entrepreneurs and new business formation to the economy. Understanding the forces underlying the formation of entrepreneurial clusters—particularly of a high growth, innovation-driven nature—is of critical interest to economists and policy-makers alike. In this paper, we build upon the seminal work of Kortum and Lerner (2000), providing evidence of the complementary side of a virtuous cycle in which innovation and capital feed upon each other: innovative activity attracts venture capital financing, which in turn finances the creation and growth of companies based on this innovation, which in turn leads to the production of additional innovation, further feeding the cycle.

Our findings have several policy implications. First, intellectual property policy that provides incentives for the commercialization of university innovation appears to have positive effects for the local economies nearby. Not only does the new access to university innovation after Bayh Dole increase local agglomeration of related industries (Hausman 2022), but also, as we show in this paper, the resulting rise in local innovative activity draws venture capital, a crucial input for the high growth entrepreneurs working to develop university related ideas. The role of VC in this next step on the path of ideas from universities to private sector innovation is likely to be vital: VC is present in all highly successful clusters of innovation, and we provide evidence suggestive of its role in university-related high growth entrepreneurship. The Bayh Dole Act thus released valuable innovation to university economies after 1980, creating the opportunity for VC dollars—which may otherwise have gone to feed established corporate innovation—to hone in on the frontier innovation being developed around universities.

Second, our results are relevant to policy makers seeking to cultivate IDE ecosystems. Because VC funding has been shown to lead to innovative activity (Kortum and Lerner 2000), and because VC funds invest disproportionately locally (Chen et al. 2010), the ability to draw VC to a region to support future innovation activity is essential. We bring new identification to the question of whether local innovation can attract VC, showing that a positive shock to frontier innovation indeed draws capital, which in turn feeds further innovative output. The importance of strong local innovation may be one reason why policy efforts to provide seed capital or attract venture capital to a region—such as tax breaks for early stage investment and the formation of local government backed funds—have met with mixed success (Lerner 2009; Denes et al. 2023). The evidence in this paper suggests that spending money on programs to encourage local innovation may be more productive in developing local ecosystems than spending on programs to create venture funds directly. Specifically, by encouraging formal technology transfer, informal knowledge sharing, and density of skilled workers, policy makers can harness the substantial power universities have to stimulate local high growth entrepreneurial clusters.

REFERENCES

Agrawal, Ajay, Iain Cockburn, and Carlos Rosell. 2010. "Not Invented Here? Innovation in Company Towns." *Special Issue: Cities and Entrepreneurship* 67 (1): 78–89.

Agrawal, Ajay, Devesh Kapur, and John McHale. 2008. "How Do Spatial and Social Proximity Influence Knowledge Flows? Evidence from Patent Data." *Journal of Urban Economics* 64: 258–69.

Botelho, Tristan L., Daniel Fehder, and Yael Hochberg. 2021. "Innovation-Driven Entrepreneurship." National Bureau of Economic Research.

Cantoni, Davide, and Noam Yuchtman. 2014. "Medieval Universities, Legal Institutions, and the Commercial Revolution." *The Quarterly Journal of Economics* 129 (2): 823–87.

Chen, Henry, Paul A. Gompers, Anna Kovner, and Josh Lerner. 2010. "Buy Local? The Geography of Venture Capital." *Journal of Urban Economics* 67 (1): 90–102. https://doi.org/10.1016/j.jue.2009.09.013.

Davis, Steven J., and John Haltiwanger. 1992. "Gross Job Creation, Gross Job Destruction, and Employment Reallocation." *The Quarterly Journal of Economics* 107 (3): 819–63. https://doi.org/10.2307/2118365.

Davis, Steven J., John C. Haltiwanger, and Scott Schuh. 1998. *Job Creation and Destruction*. *MIT Press Books*. Vol. 1. The MIT Press. https://ideas.repec.org/b/mtp/titles/0262540932.html.

Decker, Ryan A., John Haltiwanger, Ron Jarmin, and Javier Miranda. 2014. "The Role of Entrepreneurship in US Job Creation and Economic Dynamism." *Journal of Economic Perspectives* 28 (3): 3–24. https://doi.org/10.1257/jep.28.3.3.

Denes, Matthew R., Sabrina T. Howell, Filippo Mezzanotti, Xinxin Wang, and Ting Xu. 2023. "Investor Tax Credits and Entrepreneurship: Evidence from U.S. States." *The Journal of Finance* Forthcoming. https://doi.org/10.3386/w27751.

Duranton, Gilles, and Diego Puga. 2001. "Nursery Cities: Urban Diversity, Process Innovation, and the Life Cycle of Products." *American Economic Review* 91 (5): 1454–77.

Ellison, Glenn, Edward L. Glaeser, and William R. Kerr. 2010. “What Causes Industry Agglomeration? Evidence from Coagglomeration Patterns.” *American Economic Review* 100 (3): 1195–1213.

Fairlie, Robert W., Javier Miranda, and Nikolas Zolas. 2019. “Measuring Job Creation, Growth, and Survival among the Universe of Start-Ups in the United States Using a Combined Start-up Panel Data Set.” *ILR Review* 72 (5): 1262–77. https://doi.org/10.1177/0019793919862764.

Feldman, Maryann, Irwin Feller, Janet Bercovitz, and Richard Burton. 2002. “Equity and the Technology Transfer Strategies of American Research Universities.” *Management Science* 48 (1): 105–21. https://doi.org/10.1287/mnsc.48.1.105.14276.

Glaeser, Edward L., Hedi D. Kallal, Jose A. Scheinkman, and Andrei Shleifer. 1992. “Growth in Cities.” *Journal of Political Economy* 100 (6): 1126–52.

Glaeser, Edward L., Sari Pekkala Kerr, and William R. Kerr. 2015. “Entrepreneurship and Urban Growth: An Empirical Assessment with Historical Mines.” *The Review of Economics and Statistics* 97 (2): 498–520. https://doi.org/10.1162/REST_a_00456.

Glaeser, Edward L., and William R. Kerr. 2009. “Local Industrial Conditions and Entrepreneurship: How Much of the Spatial Distribution Can We Explain?” *Journal of Economics & Management Strategy* 18 (3): 623–63. https://doi.org/10.1111/j.1530-9134.2009.00225.x.

Glaeser, Edward L., William R. Kerr, and G. A. M. Ponzetto. 2010. “Clusters of Entrepreneurship.” *Journal of Urban Economics* 67 (1): 150–68.

Goldin, Claudia, and Lawrence F. Katz. 2009. *The Race between Education and Technology*. Harvard University Press.

Greenstone, Michael, Richard Hornbeck, and Enrico Moretti. 2010. “Identifying Agglomeration Spillovers: Evidence from Winners and Losers of Large Plant Openings.” *Journal of Political Economy* 118 (3): 536–98. https://doi.org/10.1086/653714.

Guzman, Jorge, and Scott Stern. 2020. “The State of American Entrepreneurship: New Estimates of the Quantity and Quality of Entrepreneurship for 32 US States, 1988–2014.” *American Economic Journal: Economic Policy* 12 (4): 212–43.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg. 2001. *The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools*. National Bureau of Economic Research.

Haltiwanger, John, Ron S. Jarmin, and Javier Miranda. 2013. “Who Creates Jobs? Small versus Large versus Young.” *Review of Economics and Statistics* 95 (2): 347–61.

Hausman, Naomi. 2020. “Entrepreneurs and City Growth.” *Maurice Falk Institute for Economic Research in Israel. Discussion Paper Series.*, no. 7: 0_1-2B.

———. 2022. “University Innovation and Local Economic Growth.” *Review of Economics and Statistics* 104 (4): 718–35.

Henderson, Rebecca, Adam B. Jaffe, and Manuel Trajtenberg. 1998. “Universities as a Source of Commercial Technology: A Detailed Analysis of University Patenting, 1965–1988.” *The Review of Economics and Statistics* 80 (1): 119–27. https://doi.org/10.1162/003465398557221.

Jaffe, Adam B., Manuel Trajtenberg, and Rebecca Henderson. 1993. “Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations.” *The Quarterly Journal of Economics* 108 (3): 577–98. https://doi.org/10.2307/2118401.

Jovanovic, Boyan, and Glenn M. MacDonald. 1994. "The Life Cycle of a Competitive Industry." *Journal of Political Economy* 102 (2): 322–47. https://doi.org/10.1086/261934.

Kantor, Shawn, and Alexander Whalley. 2014. "Knowledge Spillovers from Research Universities: Evidence from Endowment Value Shocks." *The Review of Economics and Statistics* 96 (1): 171–88. https://doi.org/10.1162/REST_a_00357.

Kaplan, Steven N., and Josh Lerner. 2010. "It Ain't Broke: The Past, Present, and Future of Venture Capital." *Journal of Applied Corporate Finance* 22 (2): 36–47. https://doi.org/10.1111/j.1745-6622.2010.00272.x.

Kerr, William R. 2008. "Ethnic Scientific Communities and International Technology Diffusion." *The Review of Economics and Statistics* 90 (3): 518–37.

———. 2010. "Breakthrough Inventions and Migrating Clusters of Innovation." *Journal of Urban Economics*, Special Issue: Cities and Entrepreneurship, 67 (1): 46–60. https://doi.org/10.1016/j.jue.2009.09.006.

Kortum, Samuel, and Josh Lerner. 2000. "Assessing the Contribution of Venture Capital to Innovation." *The RAND Journal of Economics* 31 (4): 674–92. https://doi.org/10.2307/2696354.

Lach, Saul, and Mark Schankerman. 2008. "Incentives and Invention in Universities." *The RAND Journal of Economics* 39 (2): 403–33. https://doi.org/10.1111/j.0741-6261.2008.00020.x.

Lazear, Edward P. 1997. "Incentives in Basic Research." *Journal of Labor Economics* 15 (1, Part 2): S167–97.

Lerner, Josh. 1995. "Venture Capitalists and the Oversight of Private Firms." *The Journal of Finance* 50 (1): 301–18. https://doi.org/10.1111/j.1540-6261.1995.tb05175.x.

———. 2009. *Boulevard of Broken Dreams: Why Public Efforts to Boost Entrepreneurship and Venture Capital Have Failed--and What to Do About It*. Princeton University Press.

Marshall, Alfred. 1890. "'Some Aspects of Competition.' The Address of the President of Section F-- Economic Science and Statistics--of the British Association, at the Sixtiet Meeting, Held at Leeds, in September, 1890." *Journal of the Royal Statistical Society* 53 (4): 612–43. https://doi.org/10.2307/2979546.

Moretti, Enrico. 2004. "Workers' Education, Spillovers, and Productivity: Evidence from Plant-Level Production Functions." *American Economic Review* 94 (3): 656–90. https://doi.org/10.1257/0002828041464623.

Mowery, David C, Richard R Nelson, Bhaven N Sampat, and Arvids A Ziedonis. 2001. "The Growth of Patenting and Licensing by U.S. Universities: An Assessment of the Effects of the Bayh–Dole Act of 1980." *Research Policy* 30 (1): 99–119. https://doi.org/10.1016/S0048-7333(99)00100-6.

Mowery, David C, and Bhaven N Sampat. 2001. "University Patents, Patent Policies, and Patent Policy Debates in the USA, 1925-1980." *Industrial and Corporate Change* 10 (3): 781–814.

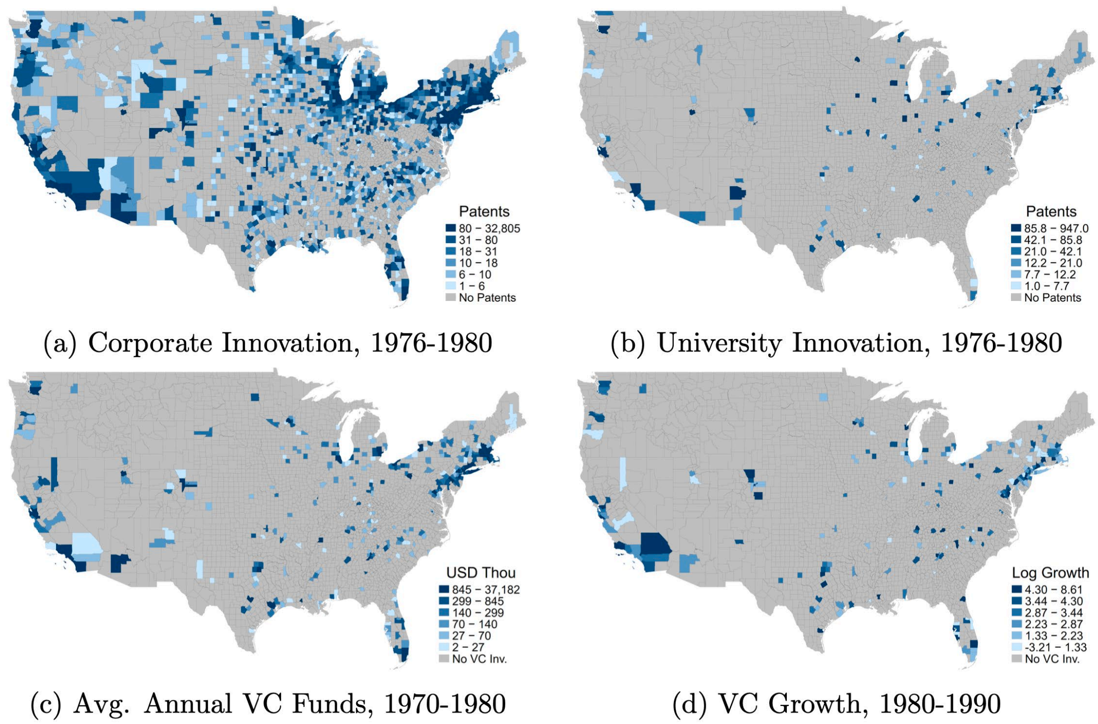
Mowery, David C., and Arvids A. Ziedonis. 2000. "Numbers, Quality, and Entry: How Has the Bayh-Dole Act Affected US University Patenting and Licensing?" *Innovation Policy and the Economy* 1: 187–220.

PwC MoneyTree. 2019. "PwC MoneyTree Report." PwC MoneyTree. 2019. https://www.pwc.com/us/en/industries/technology/moneytree.html.

Samila, Sampsa, and Olav Sorenson. 2010. "Venture Capital, Entrepreneurship, and Economic Growth." *The Review of Economics and Statistics* 93 (1): 338–49. https://doi.org/10.1162/REST_a_00066.

Sampat, Bhaven N. 2006. “Patenting and US Academic Research in the 20th Century: The World before and after Bayh-Dole.” *Property and the Pursuit of Knowledge: IPR Issues Affecting Scientific Research* 35 (6): 772–89. https://doi.org/10.1016/j.respol.2006.04.009.
Sampat, Bhaven N., David C. Mowery, and Arvids A. Ziedonis. 2003. “Changes in University Patent Quality after the Bayh–Dole Act: A Re-Examination.” *The Economics of Intellectual Property at Universities* 21 (9): 1371–90. https://doi.org/10.1016/S0167-7187(03)00087-0.
Shane, Scott. 2004. *Academic Entrepreneurship*. Northampton: Edward Elgar Publishing.
Silverman, Brian S. 1999. “Technological Resources and the Direction of Corporate Diversification: Toward an Integration of the Resource-Based View and Transaction Cost Economics.” *Management Science* 45 (8): 1109–24. https://doi.org/10.1287/mnsc.45.8.1109.
Thursby, Jerry G., Richard Jensen, and Marie C. Thursby. 2001. “Objectives, Characteristics and Outcomes of University Licensing: A Survey of Major U.S. Universities.” *The Journal of Technology Transfer* 26 (1): 59–72. https://doi.org/10.1023/A:1007884111883.
Thursby, Jerry G., and Sukanya Kemp. 2002. “Growth and Productive Efficiency of University Intellectual Property Licensing.” *Research Policy* 31 (1): 109–24.
Thursby, Jerry G., and Marie C. Thursby. 2007. “University Licensing.” *Oxford Review of Economic Policy* 23 (4): 620–39.

Figure 1: The Geography of Innovation and Venture Capital



(a) Corporate Innovation, 1976-1980

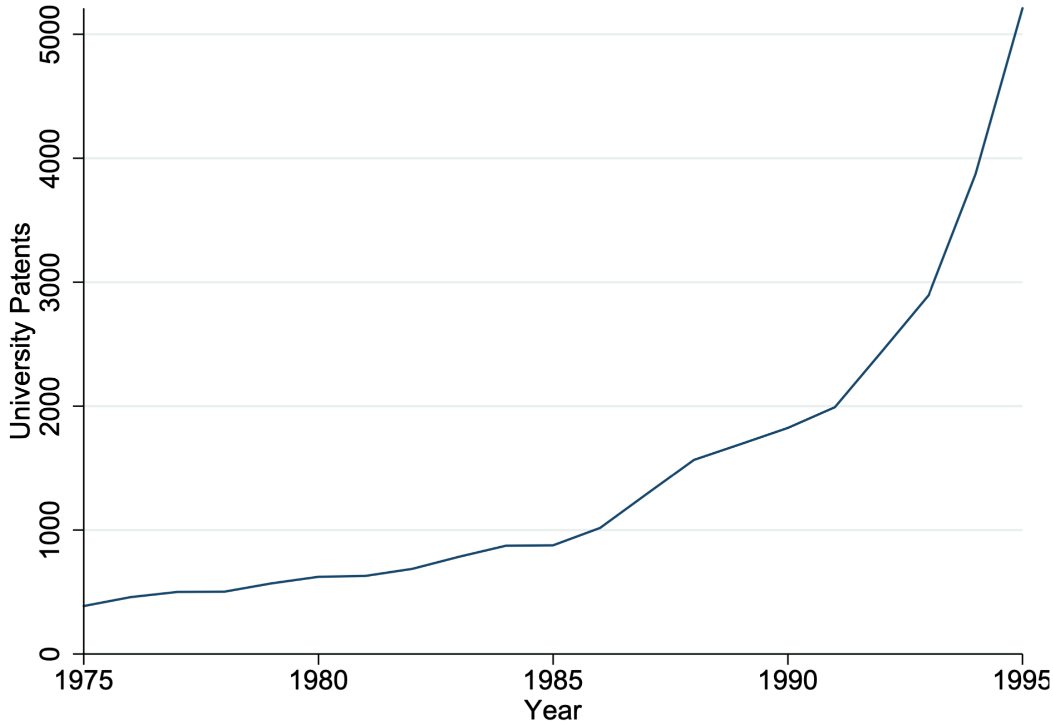
(b) University Innovation, 1976-1980

(c) Avg. Annual VC Funds, 1970-1980

(d) VC Growth, 1980-1990

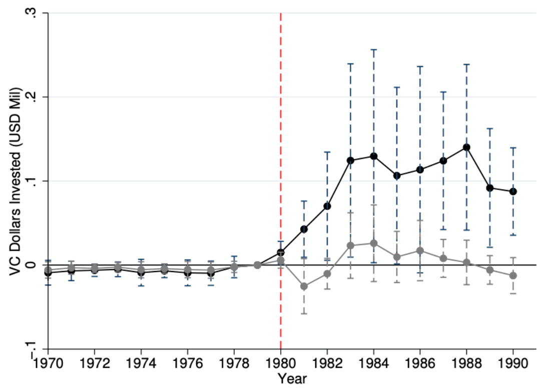
Notes: Panels (a) and (b) show, respectively, total corporate and university citation-weighted patents by county, over the years 1976-1980. Panel (c) shows average annual VC funds invested by county in the eleven years from 1970-1980. Panel (d) shows log growth in VC funds invested from 1980 to 1990, using five-year averages for each end year since many counties don't receive VC investment in any particular year. Gray areas have no patents or no VC investment, depending on the panel. Patent data are from the NBER Patent Data Project; VC data are from VentureXpert. The Bayh-Dole Act was passed in December 1980.

Figure 2: University Patenting, 1975-1995

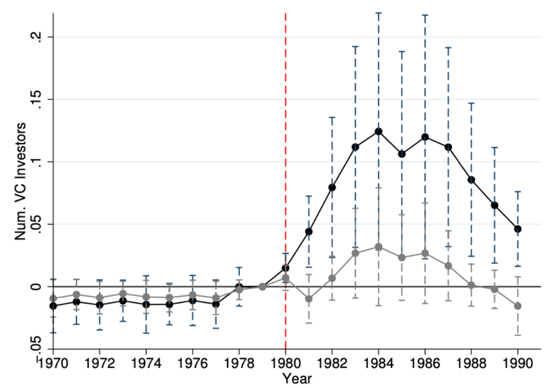


Notes: Figure shows annual number of patents produced by research universities and hospitals, by year, from the NBER Patent Database.

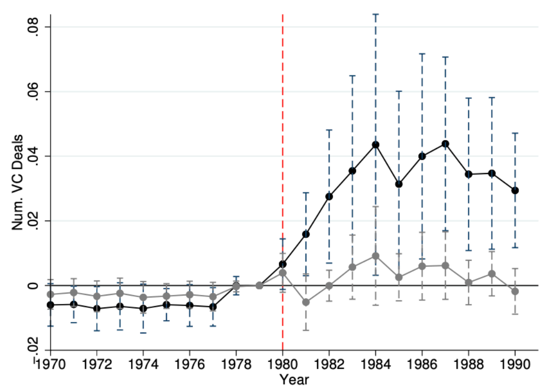
Figure 3: VC in University and Non-University Counties



(a) VC Dollars Invested (mil.)



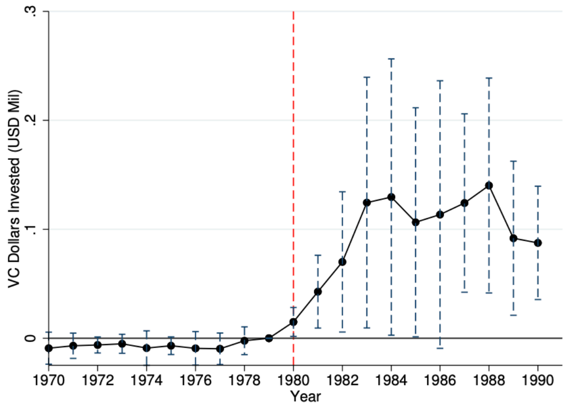
(b) Num. Investors



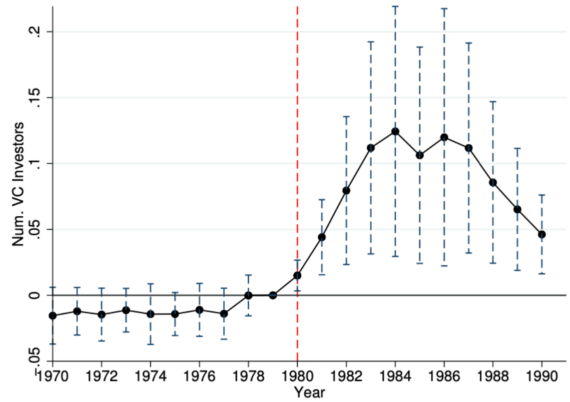
(c) Num. Deals

Notes: Figure shows raw means of VC outcomes by year in university (dark curve) and non-university counties (gray curve). University counties are defined as those containing a top 100 university or research hospital, in terms of patenting during the research period. 75 counties contain the top 100 universities.

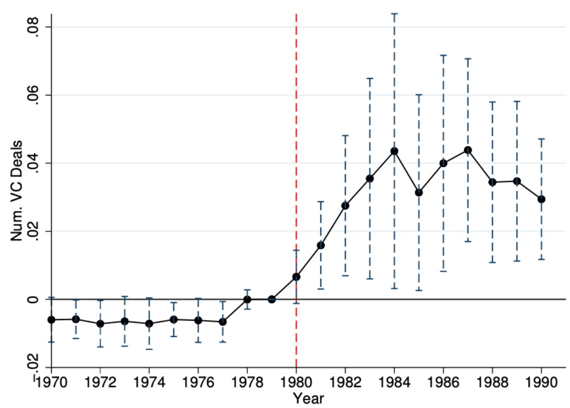
Figure 4: University Innovation Effects on Venture Capital Outcomes



(a) VC Dollars Invested (mil.)



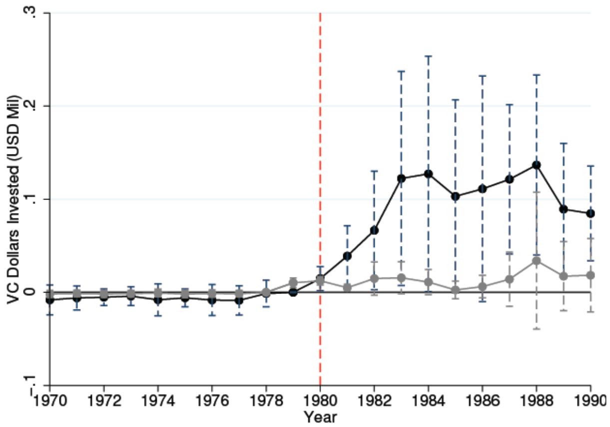
(b) Num. Investors



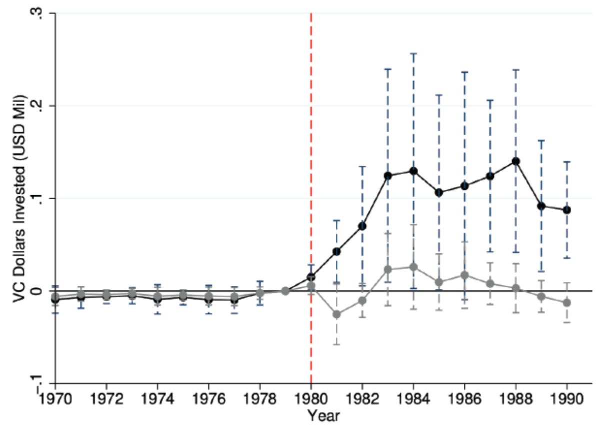
(c) Num. Deals

Notes: Points represent coefficients on university innovation index X year indicators in a version of Equation (5) that is expanded to estimate treatment effects separately by year. Each point thus reflects the effect of ex-ante university innovation on the VC outcome indicated in a particular county-industry and year. In Panel (a), the outcome variable is total VC dollars invested (in millions), in Panel (b), the number of unique VC investors, in Panel (c), the number of VC deals done. All regressions control for the interaction of corporate innovation index X $I^{year>1980}$. All regressions include fixed effects for county-industry, county-year, and industry-year. Error bars indicate 95% confidence intervals.

Figure 5: University, Ex Ante VC and Corporate Innovation Effects on VC Allocation



(a) Univ. Innovation Index vs ex ante VC Index



(b) Univ. Innovation Index vs Corp. Innovation Index

Notes: Points on the dark curve in Panel (a) represent coefficients on university innovation index X year indicators in a version of equation (4) that's expanded to estimate university treatment effects separately by year while the points on the dark curve in Panel (b) are constructed analogously from equation (5). Each point thus reflects the effect of ex-ante university innovation on the VC outcome indicated in a particular county-industry and year. In Panel (a), the points on the gray curves, analogously, represent coefficients on ex ante VC index X year indicators in a version of Equation (4) that's expanded to estimate ex ante VC treatment effects separately by year. In Panel (b), the points on the gray curves, analogously, represent coefficients on corporate innovation index X year indicators in a version of Equation (5) that's expanded to estimate corporate treatment effects separately by year. Dark curve regressions control for the interaction of ex ante VC index X $I^{year>1980}$ (Panel (a)) or corporate innovation index X $I^{year>1980}$ (Panel (b). All gray curve regressions control for the interaction of university innovation index X $I^{year>1980}$. All regressions include fixed effects for county-industry, county-year, and industry-year. Error bars indicate 95% confidence intervals.

Table 1: Descriptive Statistics

Panel A: 1970-1995 County-Industry Level Statistics

Variable	N	mean	sd	min	max
VC Dollars Invested (mil.)	14,314,457	0.01	0.89	0.00	2554.80
VC Dollars Invested (mil.), Univ. Counties	808,496	0.04	1.92	0.00	548.00
Num. VC Deals	14,314,457	0.00	0.16	0.00	131.00
Num. VC Deals, Univ. Counties	808,496	0.02	0.59	0.00	131.00
Num. VC Investors	14,314,457	0.00	0.29	0.00	167.00
Num. VC Investors, Univ. Counties	808,496	0.03	1.08	0.00	167.00
Cit-Wt Corp. Patents	14,314,457	0.64	19.91	0.00	18681.50
Cit-Wt Corp. Patents, Univ. Counties	808,496	5.50	69.16	0.00	18681.50
Uni. Innov. Index	14,314,457	0.00	1.12	-0.02	251.68
Corp. Innov. Index	14,314,457	0.00	1.00	-0.05	168.41
Ex-Ante VC Index (R&D-Scaled Funds)	13,957,171	0.00	1.12	0.00	780.80
Ex-Ante VC Index (R&D-Scaled Investors)	13,957,171	0.00	1.12	0.00	533.24

Panel B: Pre-1979 County Level Statistics, University Counties

Variable	N	mean	sd	min	max
VC Dollars Invested per County (mil.)	75	0.96	3.03	0.00	23.12
VC Deals per County	75	1.02	3.02	0.00	21.22
VC Investors per County	75	1.79	5.89	0.00	43.44

Panel C: County Level Growth Statistics, University Counties

Variable	N	mean	sd	min	max
Industries per County	75	414.61	2.35	400.00	415.00
Any VC in County, 1970-1979	75	0.55	0.00	0.00	1.00
Any VC in County, 1980-1990	75	0.80	0.00	0.00	1.00
County VC Funds, 1970	75	0.67	2.23	0.00	14.86
County VC Funds, 1995	75	61.75	173.98	0.00	1070.03
Avg. Base Funds (1/2 x (1970+1995))	75	31.21	88.05	0.00	542.45
Funds Diff, 1995-1970	75	61.09	171.88	-0.59	1055.17
County VC Deals, 1970	75	0.93	2.95	0.00	18.00
County VC Deals, 1995	75	13.99	42.35	0.00	307.00
Avg. Base Deals (1/2 x (1970+1995))	75	7.46	22.53	0.00	162.50
Deals Diff, 1995-1970	75	13.05	39.67	0.00	289.00
County VC Investors, 1970	75	1.27	4.03	0.00	24.00
County VC Investors, 1995	75	20.37	64.05	0.00	472.00
Avg. Base Investors (1/2 x (1970+1995))	75	10.82	33.84	0.00	248.00
Investors Diff, 1995-1970	75	19.11	60.48	0.00	448.00

Table 2: VC Outcomes in University vs. Non-University Counties

	Univ. Counties Treated			Univ. & Adj. Counties Treated		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	VC Funds ($ Mil.)	Num. Deals	Num. Investors	VC Funds ($ Mil.)	Num. Deals	Num. Investors
$I^{Yr \geq 1980}$ × Univ. County	0.0622***	0.0209***	0.0406**			
	(0.0224)	(0.00801)	(0.0164)			
$I^{Yr \geq 1980}$ × Univ. or Adj. County				0.0177***	0.00609***	0.0124***
				(0.00409)	(0.00144)	(0.00300)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	No	No	No	No	No	No
Observations	17,779,923	17,779,923	17,779,923	18,746,898	18,746,898	18,746,898
Window	1970-1995	1970-1995	1970-1995	1970-1995	1970-1995	1970-1995
Adj R-sq.	0.0881	0.533	0.495	0.402	0.553	0.519

Notes: An observation in the sample is a county-industry-year for the years 1970-1995. Regressions predict dependent variable indicated in a county-industry-year and include fixed effects for industry-year and county-industry in addition to the regressors shown. County-year effects are collinear with the interaction of interest and are thus not included. In columns 1-3, university containing counties are considered to be treated. In columns 4-6, counties containing universities and adjacent counties are considered to be treated. Standard errors are clustered by county. * indicates significance at the 10% level, ** at 5%, and ***at 1%.

Table 3: University Innovation and VC Outcomes

Panel A: Levels

VARIABLES	(1) VC Funds ($ Mil.)	(2) VC Funds ($ Mil.)	(3) Num. Investors	(4) Num. Investors	(5) Num. Deals	(6) Num. Deals
$I^{Yr\geq 1980}$ × Univ. Innov. Index	0.118**		0.0871**		0.0373**	
	(0.0471)		(0.0343)		(0.0145)	
$I^{Yr\geq 1980}$ × Univ. Cit-Wt Innov. Index		0.0535**		0.0396**		0.0169**
		(0.0214)		(0.0156)		(0.00659)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,314,457	14,314,457	14,314,457	14,314,457	14,314,457	14,314,457
Window	1970-1995	1970-1995	1970-1995	1970-1995	1970-1995	1970-1995
R-sq.	0.0934	0.0934	0.527	0.527	0.554	0.554

Panel B: Elasticities

VARIABLES	(1) Log (1+VC Funds ($Mil.))	(2) Log (1+Num. Investors)	(3) Log (1+Num. Deals)
$I^{Yr\geq 1980}$ × Log(1 + Univ. Innov. Index)	0.0347***	0.0354***	0.0262***
	(0.0114)	(0.00955)	(0.00705)
Industry-Year FE	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes
Observations	14,314,457	14,314,457	14,314,457
Window	1970-1995	1970-1995	1970-1995
Adj R-sq.	0.279	0.378	0.407

Notes: An observation in the sample is a county-industry-year for the years 1970-1995. Regressions in Panel A predict total VC dollars (mil.) invested in a county-industry-year (columns (1)-(2)), Number of Investors (columns (3)-(4)), and Number of Deals (columns (5)-(6)). All specifications include fixed effects for county-year, industry-year, and county-industry in addition to the regressors shown. Panel B shows estimates from log-log specifications in which the dependent variables are the logs of VC Funds ($mil), VC deals, and number of unique VC investors in a county-industry-year and in which the same fixed effects are included. The university innovation index is constructed from pre-1980 innovation, as described in Section 3 of the text. The university citation weighted ("Cit-Wt") innovation index is the raw version of the standardized index. Standard errors are clustered by county. * indicates significance at the 10% level, ** at 5%, and ***at 1%.

Table 4: Federal Funding Interaction

VARIABLES	(1) VC Funds ($ Mil.)	(2) Num. Deals	(3) Num. Investors
$I^{Yr\geq 1980}$ × Univ. Innov. Index x Avg. Annual Fed. Funding	0.0013***	0.0004***	0.0009***
	(0.000)	(0.0000)	(0.0003)
$I^{Yr\geq 1980}$ × Univ. Innov. Index	0.022	0.007	0.017*
	(0.014)	(0.004)	(0.010)
Industry-Year FE	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes
Observations	17,672,239	17,672,239	17,672,239
Window	1970-1995	1970-1995	1970-1995
R-sq.	0.092	0.545	0.512

Notes: An observation in the sample is a county-industry-year for the years 1970-1995. The variable in the top row is the triple interaction of average annual federal research funding in the 5 years prior to Bayh Dole with the innovation index and an indicator that equals one after Bayh Dole. Regressions predict total VC dollars (mil.) invested in a county-industry-year (col. 1), number of VC deals (col. 2), and number of unique VC investors (col. 3), and they include fixed effects for county-year, industry-year, and county-industry in addition to the regressors shown. The university innovation index is constructed from pre-1980 innovation, as described in Section 3 of the text. Standard errors are clustered by county. * indicates significance at the 10% level, ** at 5%, and ***at 1%.

Table 5: Heterogeneity by Ex-Ante County Characteristics

VARIABLES	(1) VC Funds ($ Mil.)	(2) VC Funds ($ Mil.)	(3) VC Funds ($ Mil.)	(4) VC Funds ($ Mil.)	(5) VC Funds ($ Mil.)	(6) VC Funds ($ Mil.)	(7) VC Funds ($ Mil.)	(8) VC Funds ($ Mil.)
$I^{Yr\geq1980}$ × Univ. Innov. Index	0.00146	0.00286	0.00304	0.00165	0.000527	0.0180***	0.000870	0.00720
	(0.000954)	(0.00468)	(0.00470)	(0.00248)	(0.00147)	(0.00472)	(0.00223)	(0.00482)
Above Median Income x $I^{Yr\geq1980}$ × Univ. Innov. Index	0.119**							
	(0.0472)							
Above Median BA Shr x $I^{Yr\geq1980}$ × Univ. Innov. Index		0.115**						
		(0.0454)						
Above Median Pop x $I^{Yr\geq1980}$ × Univ. Innov. Index			0.115**					
			(0.0455)					
Above Median Urban Shr x $I^{Yr\geq1980}$ × Univ. Innov. Index				0.117**				
				(0.0464)				
Above Median Corp Innov x $I^{Yr\geq1980}$ × Univ. Innov. Index					0.121**			
					(0.0476)			
Above Median Emp x $I^{Yr\geq1980}$ × Univ. Innov. Index						0.0998**		
						(0.0439)		
Above Median Wage x $I^{Yr\geq1980}$ × Univ. Innov. Index							0.118**	
							(0.0462)	
Above Median Avg Est Size x $I^{Yr\geq1980}$ × Univ. Innov. Index								0.111**
								(0.0452)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,314,457	14,314,457	14,314,457	14,314,457	14,314,457	14,314,457	14,314,457	14,314,457
Window	1970-1995	1970-1995	1970-1995	1970-1995	1970-1995	1970-1995	1970-1995	1970-1995
Adj R-sq.	0.0935	0.0934	0.0934	0.0934	0.0935	0.0934	0.0934	0.0934

Notes: An observation in the sample is a county-industry-year for the years 1970-1995. Each column represents a separate regression of VC dollars invested (mil.) on the interaction of university innovation index with an indicator for post Bayh-Dole and on the triple interaction of that with an indicator for a county that was above median on the indicated variable as of 1980. All regressions include fixed effects for county-year, industry-year, and county-industry in addition to the regressors shown. The university innovation indices are constructed from pre-1980 innovation, as described in Section 3 of the text. Demographic data are from the US decennial census, accessed via NHGIS. Employment, wage, and average establishment size are from County Business Patterns. Corporate innovation is based on NBER patent data. Standard errors are clustered at the county level. * indicates significance at the 10% level, ** at 5%, and ***at 1%.

Table 6: Comparison of University Innovation, Ex-Ante VC, and Corporate Innovation Effects

	University & Ex-Ante VC Effects			University & Ex-Ante Corp. Innov. Effects			Three-way Comparison		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	VC Funds ($ Mil.)	Num. Deals	Num. Investors	VC Funds ($ Mil.)	Num. Deals	Num. Investors	VC Funds ($ Mil.)	Num. Deals	Num. Investors
$I^{Yr\geq 1980}$ × Univ. Innov. Index	0.116**	0.0367**	0.0860**	0.117**	0.0366**	0.0852**	0.115**	0.0359**	0.0840**
	(0.0477)	(0.0147)	(0.0346)	(0.0462)	(0.0143)	(0.0338)	(0.0468)	(0.0145)	(0.0342)
$I^{Yr\geq 1980}$ × Ex-Ante VC Index	0.0295	0.00924	0.0161*				0.0295	0.00927	0.0162*
	(0.0215)	(0.00580)	(0.00907)				(0.0215)	(0.00584)	(0.00918)
$I^{Yr\geq 1980}$ × Corp. Innov. Index				0.00157	0.00218	0.00632	0.00218	0.00237	0.00665
				(0.0108)	(0.00341)	(0.00891)	(0.0106)	(0.00339)	(0.00892)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,957,071	13,957,071	13,957,071	14,314,457	14,314,457	14,314,457	13,957,071	13,957,071	13,957,071
Window	1970-1995	1970-1995	1970-1995	1970-1995	1970-1995	1970-1995	1975-1990	1970-1995	1970-1995
R-sq.	0.100	0.558	0.531	0.0934	0.554	0.527	0.100	0.558	0.532

Notes: An observation in the sample is a county-industry-year for the years 1970-1995. All regressions include fixed effects for county-year, industry-year, and county-industry in addition to the regressors shown. The university and corporate innovation indices are constructed from pre-1980 innovation, and the VC index is constructed from pre-1979 VC investment locations and industries, as described in Section 3 of the text. Standard errors are clustered at the county level. $*$ denotes significance at the 10% level, $**$ at the 5%, and $***$ at the 1%.

Table 7: Predictors of Post-ERISA, Post-Bayh-Dole Corporate Innovation

	DV: Citation Weighted Corporate Patents			
	(1)	(2)	(3)	(4)
$I^{Yr\geq 1980}$ × Univ. Innov. Index	6.660**			4.576*
	(2.774)			(2.686)
$I^{Yr\geq 1980}$ × Ex-Ante VC Index		0.255***		-0.137
		(0.088)		(0.131)
$I^{Yr\geq 1980}$ × Corp. Innov. Index			8.626***	6.824*
			(3.877)	(3.546)
Industry-Year FE	Yes	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes
Observations	13,957,071	13,957,071	13,957,071	13,957,071
Window	1970-1995	1970-1995	1970-1995	1970-1995
R-sq.	0.601	0.568	0.611	0.625

Notes: An observation in the sample is a county-industry-year for the years 1970-1995. Regressions predict citation-weighted corporate patents in a county-industry-year and include fixed effects for county-year, industry-year, and county-industry in addition to the regressors shown. The university and corporate innovation indices are constructed from pre-1980 innovation, and the VC index is constructed from pre-1979 VC investor and investment locations and industries, as described in Section 3 of the text. Standard errors are clustered at the county level. * indicates significance at the 10% level, ** at 5%, and ***at 1%.

Table 8: University Counties, Federal Research Funding, and High Growth Entrepreneurship

Panel A: University vs. Non-University Counties

	(1) Entrants with Eventual Growth Events	(2) Quality-adj. Quantity of Entrep. Entrants	(3) Entrant Quality Index	(4) Realized-to-Exp. Eventual Growth Events
Univ. County	2.693***	1.253***	0.000***	0.776***
	(0.854)	(0.301)	(0.000)	(0.267)
Year FE	Yes	Yes	Yes	Yes
Observations	22,038	22,038	22,038	22,038
Window	1970-1995	1970-1995	1970-1995	1970-1995
Adj R-sq.	0.078	0.122	0.002	-0.000

Panel B: By Federal Research Funding

	(1) Entrants with Eventual Growth Events	(2) Quality-adj. Quantity of Entrep. Entrants	(3) Entrant Quality Index	(4) Realized-to-Exp. Eventual Growth Events
Avg. Annual Federal Research Funding ($ mil)	0.056***	0.025***	0.000***	0.011***
	(0.019)	(0.007)	(0.000)	(0.004)
Year FE	Yes	Yes	Yes	Yes
Observations	22,038	22,038	22,038	22,038
Window	1970-1995	1970-1995	1970-1995	1970-1995
Adj R-sq.	0.078	0.122	0.002	-0.000

Notes: An observation in the sample is a county-year for the years 1988-1995. Regressions predict new business registrations of firms with eventual growth events in columns (1)-(2), the quality of entrants in terms of likelihood of growth in column (3) and actual-to-expected eventual growth events in column (4). All outcomes are future-measured events of current year new business registrants. Regressions include year fixed effects. University County is an indicator for counties containing top 100 research universities or hospitals. Average Annual Federal Research Funding ($mil.) reflects the funding received by each of these top 100 innovating institutions in the five years leading up to Bayh Dole. VC dollars invested ($mil.) are measured contemporaneously with the entrepreneurial entry outcomes.
* indicates significance at the 10% level, ** at 5%, and ***at 1%.

Table 9: University Innovation, VC, and High Growth Entrepreneurship

	Entrants with Eventual Growth Events			Realized-to-Expected Eventual Growth Events		
	(1)	(2)	(3)	(4)	(5)	(6)
Univ. Innov Index	0.733***	0.651**	0.220*	0.139***	0.127**	–0.005
	(0.270)	(0.262)	(0.122)	(0.052)	(0.052)	(0.022)
Corp. Innov Index		0.211	–0.125***		0.031	–0.061***
		(0.154)	(0.034)		(0.032)	(0.016)
VC Dollars Invested ($Mil)			0.038***			0.013***
			(0.009)			(0.002)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	21,968	21,968	21,968	21,968	21,968	21,968
R-Sq	0.357	0.380	0.671	0.000	0.000	0.000

Note: An observation in the sample is a county-year for the years 1988-1995. Regressions predict new business registrations of firms with growth events in columns (1)-(3) and actual-to-expected growth events in columns (4)-(6). Regressions include year fixed effects, and columns (3) and (6) control for 1980 county population. The university and corporate innovation indices are constructed from pre-1980 innovation, as described in Section 3 of the text. VC dollars invested are measured contemporaneously with the entrepreneurial entry outcomes. * indicates significance at the 10% level, ** at 5%, and ***at 1%.

APPENDIX FIGURES AND TABLES

Figure A1: Illustrative Example Explaining Construction of the Innovation Index

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

Concordance

Patent Class	SIC3	weight
12300	111	0.20
	222	0.00
	333	0.20
	444	0.45
	555	0.15
12301	111	0.00
	222	0.05
	333	0.40
	444	0.10
	555	0.45

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

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 indeces 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 indeces (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.

Table A1: University Innovation and VC Outcomes with 1975-1990 Window

Panel A: Levels

VARIABLES	(1) VC Funds ($ Mil.)	(2) VC Funds ($ Mil.)	(3) Num. Investors	(4) Num. Investors	(5) Num. Deals	(6) Num. Deals
$I^{Yr\geq1980}$ × Univ. Innov. Index	0.106**		0.0955**		0.0363**	
	(0.0476)		(0.0380)		(0.0141)	
$I^{Yr\geq1980}$ × Univ. Cit-Wt Innov. Index		0.0480**		0.0434**		0.0165**
		(0.0216)		(0.0172)		(0.00640)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,704,079	8,704,079	8,704,079	8,704,079	8,704,079	8,704,079
Window	1975-1990	1975-1990	1975-1990	1975-1990	1975-1990	1975-1990
R-sq.	0.0760	0.0760	0.592	0.592	0.628	0.628

Panel B: Elasticities

VARIABLES	(1) Log (1+VC Funds ($Mil.))	(2) Log (1+Num. Investors)	(3) Log (1+Num. Deals)
$I^{Yr\geq1980}$ × Log(1 + Univ. Innov. Index)	0.0349***	0.0366***	0.0259***
	(0.0112)	(0.00955)	(0.00664)
Industry-Year FE	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes
Observations	8,704,079	8,704,079	8,704,079
Window	1975-1990	1975-1990	1975-1990
Adj R-sq.	0.334	0.429	0.465

Notes: This table repeats the analysis of Table 3 in the main results with time window from 1975 through 1990. An observation in the sample is a county-industry-year for the years 1970-1995. Regressions in Panel A predict total VC dollars (mil.) invested in a county-industry-year (columns (1)-(2)), Number of Investors (columns (3)-(4)), and Number of Deals (columns (5)-(6)). All specifications include fixed effects for county-year, industry-year, and county-industry in addition to the regressors shown. Panel B shows estimates from log-log specifications in which the dependent variables are the logs of VC Funds ($mil), VC deals, and number of unique VC investors in a county-industry-year and in which the same fixed effects are included. The university innovation index is constructed from pre-1980 innovation, as described in Section 3 of the text. The university citation weighted ("Cit-Wt") innovation index is the raw version of the standardized index. Standard errors are clustered by county. * indicates significance at the 10% level, ** at 5%, and ***at 1%.

Table A2: University Innovation and VC Outcomes Top 200 Research Universities and Hospitals Included

Panel A: Levels

VARIABLES	(1) VC Funds ($ Mil.)	(2) VC Funds ($ Mil.)	(3) Num. Investors	(4) Num. Investors	(5) Num. Deals	(6) Num. Deals
$I^{Yr\geq1980}$ × Univ. Innov. Index	0.117**		0.0869**		0.0372**	
	(0.0470)		(0.0342)		(0.0145)	
$I^{Yr\geq1980}$ × Univ. Cit-Wt Innov. Index		0.0531**		0.0393**		0.0168**
		(0.0213)		(0.0155)		(0.00655)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,314,457	14,314,457	14,314,457	14,314,457	14,314,457	14,314,457
Window	1970-1995	1970-1995	1970-1995	1970-1995	1970-1995	1970-1995
R-sq.	0.0933	0.0933	0.527	0.527	0.554	0.554

Panel B: Elasticities

	(1) Log (1+VC Funds ($Mil.))	(2) Log (1+Num. Investors)	(3) Log (1+Num. Deals)
$I^{Yr\geq1980}$ × Log(1 + Univ. Innov. Index)	0.0341***	0.0348***	0.0257***
	(0.0111)	(0.00930)	(0.00688)
Observations	14,314,457	14,314,457	14,314,457
Window	1970-1995	1970-1995	1970-1995
Adj R-sq.	0.279	0.378	0.407

Notes: This table repeats the analysis of Table 3 in the main results with a data set that includes the top 200 research universities. An observation in the sample is a county-industry-year for the years 1970-1995. Regressions in Panel A predict total VC dollars (mil.) invested in a county-industry-year (columns (1)-(2)), Number of Investors (columns (3)-(4)), and Number of Deals (columns (5)-(6)). All specifications include fixed effects for county-year, industry-year, and county-industry in addition to the regressors shown. Panel B shows estimates from log-log specifications in which the dependent variables are the logs of VC Funds ($mil), VC deals, and number of unique VC investors in a county-industry-year and in which the same fixed effects are included. The university innovation index is constructed from pre-1980 innovation, as described in Section 3 of the text. The university citation weighted ("Cit-Wt") innovation index is the raw version of the standardized index. Standard errors are clustered by county. * indicates significance at the 10% level, ** at 5%, and ***at 1%.

Table A3: University Innovation and VC Outcomes Innovation Index Using Patents Until 1985

Panel A: Levels

VARIABLES	(1) VC Funds ($ Mil.)	(2) VC Funds ($ Mil.)	(3) Num. Investors	(4) Num. Investors	(5) Num. Deals	(6) Num. Deals
$I^{Yr \geq 1980}$ × 1985 Univ. Innov. Index	0.129***		0.0913***		0.0398***	
	(0.0422)		(0.0320)		(0.0133)	
$I^{Yr \geq 1980}$ × 1985 Univ. Cit-Wt Innov. Index		0.0246***		0.0175***		0.00762***
		(0.00809)		(0.00612)		(0.00255)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,244,569	14,244,569	14,244,569	14,244,569	14,244,569	14,244,569
Window	1970-1995	1970-1995	1970-1995	1970-1995	1970-1995	1970-1995
R-sq.	0.0942	0.0942	0.530	0.530	0.557	0.557

Panel B: Elasticities

	(1) Log (1+VC Funds ($Mil.))	(2) Log (1+Num. Investors)	(3) Log (1+Num. Deals)
$I^{Yr \geq 1980}$ × Log(1 + 1985 Univ. Innov. Index)	0.0235***	0.0244***	0.0179***
	(0.00736)	(0.00638)	(0.00470)
Observations	14,314,457	14,314,457	14,314,457
Window	1970-1995	1970-1995	1970-1995
Adj R-sq.	0.279	0.378	0.408

Notes: This table repeats the analysis of Table 3 in the main results with a data where university expertise across industries is calculated with patents through 1985. Regressions in Panel A predict total VC dollars (mil.) invested in a county-industry-year (columns (1)-(2)), Number of Investors (columns (3)-(4)), and Number of Deals (columns (5)-(6)). All specifications include fixed effects for county-year, industry-year, and county-industry in addition to the regressors shown. Panel B shows estimates from log-log specifications in which the dependent variables are the logs of VC Funds ($mil), VC deals, and number of unique VC investors in a county-industry-year and in which the same fixed effects are included. The university innovation index is constructed from pre-1980 innovation, as described in Section 3 of the text. The university citation weighted ("Cit-Wt") innovation index is the raw version of the standardized index. Standard errors are clustered by county. * indicates significance at the 10% level, ** at 5%, and ***at 1%.

Table A4: University Innovation and VC Outcomes at Varying Distances from the University

Panel A: VC Funds

Dependent Variable:	Funds Invested ($Mil)					
	(1)	(2)	(3)	(4)	(5)	(6)
$I^{Yr \geq 1980} \times$ Univ. Innov. Index	0.118**		0.071**		0.038**	
	(0.047)		(0.032)		(0.017)	
$I^{Yr \geq 1980} \times$ Univ. Cit-Wt Innov. Index		0.054**		0.013**		0.004**
		(0.021)		(0.006)		(0.002)
N	14,314,457	14,314,457	14,990,069	14,990,069	17,672,239	17,672,239
Radius of Innov Effects	Own Cnty	Own Cnty	Adj Cnties	Adj Cnties	75 Mile	75 Mile
R-Sq	0.093	0.093	0.405	0.405	0.091	0.091

Panel B: VC Deals and Investors

Dependent Variable:	Num. Deals			Num. Investors		
	(1)	(2)	(3)	(4)	(5)	(6)
$I^{Yr \geq 1980} \times$ Univ. Innov. Index	0.037**	0.023**	0.012**	0.087**	0.056**	0.029**
	(0.015)	(0.010)	(0.005)	(0.034)	(0.023)	(0.012)
N	14,314,457	14,990,069	17,672,239	14,314,457	14,990,069	17,672,239
Radius of Innov Effects	Own Cnty	Adj Cnties	75 Mile	Own Cnty	Adj Cnties	75 Mile
R-Sq	0.554	0.563	0.541	0.527	0.536	0.506

Table A5: University Innovation and VC Outcomes Excluding CA and MA and Excluding Top 10 Universities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. Variable	log(1+Dollars Invested (Mil.))			log(1+Num Investors)			log(1+Num Deals)		
Sample	Main Spec	No CA/MA	Ex. Top 10 Uni.	Main Spec	No CA/MA	Ex. Top 10 Uni.	Main Spec	No CA/MA	Ex. Top 10 Uni.
$I^{Yr \geq 1980}$ × Log(1 + Univ. Innov. Index)	0.0347***	0.0120***	0.0135***	0.0354***	0.0159***	0.0170***	0.0262***	0.0117***	0.0126***
	(0.0114)	(0.00362)	(0.00475)	(0.00955)	(0.00364)	(0.00475)	(0.00705)	(0.00247)	(0.00318)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,314,457	13,787,696	13,787,696	14,314,457	13,787,696	13,787,696	14,314,457	13,787,696	13,787,696
Window	1970-1995	1970-1995	1970-1995	1970-1995	1970-1995	1970-1995	1970-1995	1970-1995	1970-1995
Adj R-sq.	0.279	0.179	0.179	0.378	0.278	0.278	0.407	0.298	0.298

Notes: An observation in the sample is a county-industry-year for the years 1970-1995. Sample is identical to that in Table 3 except that it excludes California and Massachusetts in columns (2), (5), and (8) and excludes innovation from the top 10 universities in columns (3), (6), and (9). Regressions predict log(1+total VC dollars (mil.)) invested in a county-industry-year in columns (1)-(3), Log(1+Number of Investors) (columns (4)-(6)), and Log(1+Number of Deals) (columns (7)-(9)). All specifications include fixed effects for county-year, industry-year, and county-industry in addition to the regressors shown. The university innovation index is constructed from pre-1980 innovation, as described in Section 3 of the text. Standard errors are clustered by county. * indicates significance at the 10% level, ** at 5%, and ***at 1%.