THE VIRTUOUS CYCLE OF INNOVATION AND CAPITAL FLOWS*

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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 drives future innovation. Because universities have different technological strengths, each local area surrounding a university experienced an increase in innovation relevant to particular sets of industries after 1980—industries which differ widely across university counties. Comparing industries within a county that were more versus less connected 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 distribution of corporate patenting and prior venture financing in the pre-period does 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.

***** PRELIMINARY AND INCOMPLETE *****

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1. INTRODUCTION

The geographic distribution of venture capital and other forms of investment for innovation-driven entrepreneurship is highly concentrated. In 2019, Silicon Valley firms received 39% of all U.S. Venture Capital (VC) allocation; 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 IDE ecosystems and has been one of the most frequently targeted areas for intervention. While evidence of a strong association between capital and innovative activity is well-established in the literature (Kortum and Lerner, 2000), the precise nature and directionality of this association is less explored. This paper revisits the relationship between innovation and capital allocation in geographic areas and provides evidence consistent with the notion that not only might access to VC lead to increased innovative activity, as shown by Kortum and Lerner (2000) at the national level, but, equally importantly, VC itself is drawn to and deployed in a region in response to positive shocks to the supply of innovation activity.

From a policy perspective, establishing the directionality of the relationship between innovative activity and capital deployment is of significant import. Policy makers have often focused on interventions designed 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—with mixed success (Lerner 2009). 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 allow such activity to draw private investment to the region in its wake, igniting a (hopefully) virtuous cycle of clustered economic activity. Interventions designed to promote innovative activity may be more cost effective than creating a fund or offering subsidies to VCs. If innovation attracts capital, they 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.

To shed light on this direction of the innovation-capital relationship, we follow Hausman (2020a) in taking 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, and the subsequent Trademark Clarification Act which followed shortly after its passage, gave universities property rights to innovations developed at their institutions with the use of federal research funding. The Act provided strong incentives for universities to engage in patenting and licensing activity, and it led to the development of significant infrastructure for technology transfer such that university

innovation became 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 across technologies, within a geographic area, depending on the pre-Act research strengths of the nearby university. As a result, we can hold a geographic area fixed and identify effects off between-industry differences in expected growth within a county.

To build intuition for the strategy, consider the different pre-1980 innovative strengths of two strong research universities and, if innovation indeed attracts VC, what the implications of these differences would be for expected local VC growth after 1980. When Bayh Dole was passed, the University of Texas at Austin had a top electrical and computer engineering department. In contrast, Johns Hopkins University 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 BD to be larger in local electronic and computer-related industries than in pharmaceutical or bioscience-related industries, while in Baltimore, MD, the area surrounding Johns Hopkins, 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, beginning with 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 funding for venture capital firms in the early 1980s—funding which then needed to be deployed across investment opportunities in the U.S. We argue that these funds disproportionately went to university areas and related industries, and we test two leading alternative hypotheses reflecting the possibility that post-1980 VC allocations could be due to ERISA regulatory changes alone. First, these funds could have been deployed to areas with existing stocks of corporate innovation, which was much larger

in scale and more geographically pervasive than university innovation (Figure 1). Second, the influx of VC funds could have been allocated much as pre-1979 VC funds were allocated, but on a larger scale. In fact, the locations with the greatest 1980-1990 VC growth, shown in Figure 1, Panel (d), so closely resemble the locations of pre-1980 university innovation (Panel (a)) 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. The maps of pre-Bayh-Dole, pre-ERISA corporate patenting and VC funds look markedly different (Panels (b) and (c)).

We show in our formal analysis 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 $117,000 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 $21.6 million additional VC investment per county after Bayh Dole, while the average university county saw a *total* increase of $23.4 mil. in VC funding over the 20 years surrounding both Bayh Dole and the regulatory changes that increased the supply of VC funding. Bayh Dole's shock to university innovation can thus account for the vast majority of the increase in VC funding to these locations.

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 corporate innovation—which comprises the vast majority of U.S. patenting—was strong, or to the areas and industries in which VC already had a presence. What we observe, in contrast, is the flow of VC funds overwhelmingly to the regions and industries in which university innovation was strongest, even controlling for the geographic and technological distribution of corporate innovation. 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.

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 that successful entrepreneurial clusters have, and other places lack. We provide two new pieces of evidence on the effects of VC financing on innovative activity. First, following Kortum and Lerner (2000), we use the 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. Using the pre-1979 distribution of VC across geographic areas and industries, we find that ex-ante VC investment patterns strongly predict post-ERISA corporate innovation activity, but only if we do not control for the pre-1979 distribution of corporate R&D investment. Put differently, VC drives post-ERISA corporate innovation only to the extent that these investment opportunities were known as of 1979.

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-ERISA 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 (2015) 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 find exactly the high growth entrepreneurs launched by cutting edge university ideas. This new evidence illustrates the critical role of 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 related industries.

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. High quality data at detailed geographic and industry levels for both innovation and VC improves measurement of their complex relationship. Our identification strategy relies on the assumption that the industries and locations we identify as receiving the largest boost in VC allocations after Bayh-Dole weren't already on faster growth trajectories for VC funding before the Act for reasons other than university research. Hausman (2020a), who employs a similar identification strategy to measure industry growth in the wake of Bayh Dole, demonstrates using the confidential U.S. Census Longitudinal Business Database (LBD) that university-related industries and areas did not grow

differentially before the law passage, nor did corporate patenting in the relevant counties and technologies. We provide analogous evidence for VC allocations, showing that there were no differential pre-treatment trends in VC dollars invested, numbers of deals, or numbers of investors.

Our findings offer a number of contributions to the literature. First, 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 (e.g. 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 2015), 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 (Glaeser, Rosenthal, and Strange 2010; Glaeser, Kerr, and Kerr 2015; Agrawal, Cockburn, and Rosell 2010; Shane 2004). Our findings suggest that one additional tool in the policy maker's toolbox is to encourage innovation activity, while allowing commercialization to be supported by private capital that flows into the market in its wake.

Second, the 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 (Duranton and Puga 2001; Agrawal, Cockburn, and Rosell 2010) and that use of innovation is disproportionately local (Jaffe, Trajtenberg, and Henderson 1993; Kerr 2010). Hausman (2020a) provides evidence on the role of knowledge spillovers in driving increased agglomeration of related industries around universities following the increase in accessibility of their ideas after Bayh Dole. Our paper illustrates the importance, in addition, of input-output relationships in facilitating these innovative clusters around universities, as VC is a critical input for many entrepreneurs and is allocated disproportionately locally (Chen et al. 2010). Multiple sources of agglomeration economies are thus activated by the Bayh Dole university innovation shock, igniting the virtuous cycle of innovation and capital that is characteristic of successful industrial clusters.

Third, 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 2013), or knowledge spillovers (Hausman 2020a). 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 works through our several empirical analyses and their associated results. 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 (Hausman 2020a).[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

[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.

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.

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 allowing 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 (Hausman 2020a).[5]

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

[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 (2020a). 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

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 (Hausman 2020a). While only 55 universities had been granted a patent in 1976, 340 universities 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

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.

[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 (2004b)).

[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.

corporations, U.S. or foreign governments, hospitals, or universities. The subset of patents assigned to universities and university-affiliated hospitals generates our sample of innovating universities, identifies the research fields in which each university is highly innovative, and connects these research fields to the industries that may use a particular research field's innovations.[9] 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 (2020a) Innovation Index

To construct a measure of university innovation, we follow Hausman (2020a), 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, 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.

[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 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. 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.

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

The measure is then standardized to be mean zero, standard deviation one.

The resulting innovation index measure captures cross-industry differences in use of university innovation. Examples of high index industries are hospitals, drugs, medical instruments, and medical laboratories due to the strength of universities in biomedical innovation. But universities innovate more broadly, heavily affecting industries such as computers, communication equipment, measuring and controlling devices, plastics, and other chemicals. Low index industries include several in wholesale and retail trade, non-technical professional services (labor organizations, legal services), and FIRE (finance, insurance, and real estate).[11]

3.3. NSF Federal Research Funding to Universities

Data on federal research funding to universities, 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. 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 DOD and $27.2 million of which came from 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.

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

3.4. University Counties

In our main sample, we consider counties containing 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.[12]

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 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 way 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

[12] Robustness tests re-estimate the main results with a sample that allows all counties within a 75 mile radius of the university's own county to be affected by the university. In that sample, all counties within a 75 mile radius are considered ``university counties.''

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 thus 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.

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

As an alternative, we compute the same index using the number of VC investors as the numerator. We standardize both to be mean zero and standard deviation one, as with the other indices, and we refer to them as the *VC Dollar Index* and the *VC Investor Index*, respectively. The ability of these measures 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

We use data publicly provided by the Startup Cartography Project (SCP), described in detail in Guzman and Stern (2015), on high growth entrepreneurship by county. 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.[13] 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 where university counties were before the policy changes studied, Panel B offers county-level statistics for university counties prior to 1979. Panel C describes the growth in VC experienced by university counties over the sample period.

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 use a shock to innovation that is plausibly exogenous to venture capital investment in a region. In particular, we take advantage of a national policy change – the Bayh Dole Act of 1980 – that generates a shock to the spread of innovation from universities and will have different expected effects across geographical areas and industries.

4.1. University vs. Non-University Counties

We begin our analysis with a basic comparison of university counties to non-university counties before and after the passage of Bayh Dole. 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, as shown in Hausman (2020a). Figure 3 presents the raw averages of VC funds and VC investors over time for university and non-university counties. As can be seen clearly from the figure, university counties experience a larger increase in both VC dollar volume of investments and number of unique VC investors after 1980, relative to non-university counties. While the graphs for both VC measures show similar pre-treatment trends in university and non-university counties, consistent with VC funding flowing to

[13] The main sample treats only counties containing universities, while robustness tests presented in the appendix treat all counties within a 75 mile radius of the university.

areas that are "shocked" with more innovation, it is also likely that these two types of counties are different on many dimensions.

Table 2 measures this cross-county relationship more formally. We estimate variations of the model:

$$(1)\ y_{cit} = \beta_0 + \beta_1(I(year > 1980) * I(university)_c) + \vartheta_{it} + \theta_{ci} + \epsilon_{cit},$$

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 aren't 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.

We estimate the model using six variations of outcomes measures: (1) total VC investment dollars deployed in the county-industry-year (measured in $ million), (2) the natural logarithm of one plus the total VC investment dollars deployed in the county-industry-year, (3) the number of VC deals in the county-industry-year, (4) the number of unique active VC investors in the county-industry-year, and (5) the number of corporate patents in the county-industry-year, as well as the natural logarithm of one plus this count (6). Across all six specifications, we observe the same basic pattern: the amount of VC investment, the number of VC deals, the number of active VC investors, and the volume of corporate patenting activity all rise in university-containing counties post Bayh Dole, relative to non-university-containing counties. These cross-county results do not appear much larger than the county-industry level results we measure below, but of course they reflect average effects across many university county industries, most of which do not attract VC at all.

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 take advantage, in addition, 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 *Innovation Index*.

The expected differential effects of the shock on VC funding deployed in each county-industry are best illustrated by an example: at the time of Bayh Dole's passing, UT Austin, for example, was particularly strong in research in electrical and computer engineering—it has a high innovation index in that industry—and we thus expect to see VC funds flow specifically to that industry in the Austin area in the wake of the Act's passage. Similarly, Johns Hopkins University was particularly strong in biomedical sciences research, such that pharma, medical devices and other biomedical industries have high *Innovation Index* measures in the Baltimore area, and we expect more VC fund flows to investments in those industries in that location.

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 particular industries 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. $univ_index_{ci}$ is the standardized Hausman (2020a) 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. 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 presents the results of estimation of equation (2), where the outcome variable of interest is the total VC dollars invested in a county-industry-year. As can be seen from column (1), the

coefficient of interest, β_1, is positive and statistically significant. Because the innovation index is standardized to be mean 0 and standard deviation 1, the magnitudes can be read directly from the table. A one standard deviation increase in the innovation index for a given industry in a university-containing county is associated with a $118K increase in VC funding deployed in the county-industry after Bayh-Dole. Column (2) zooms in on a shorter window around the policy change, 1975-1990, and indicates that the effect is present and only slightly smaller right around the event. In column (3), we estimate the model using a non-standardized version of the innovation index to offer an additional means of scaling the treatment coefficient. This coefficient indicates that the treatment effect is equivalent to a $54K increase in VC funds per county industry per citation to a university patent. Finally, column (4) estimates the model using the natural logarithm of 1 plus VC dollars invested as the dependent variable, and results remain similar in sign and significance.

Table 4 presents estimates of equation (1) where the dependent variable is the number of VC deals in the county-industry (columns (1) and (2)) or number of unique active VC investors in the county (columns (3) and (4)). Columns (1) and (3) present estimates for the full sample period, while columns (2) and (4) zoom in on the 1975-1990 period just around the policy change. Once again, regardless of the outcome measures used, we observe a positive and significant coefficient of interest. The coefficient in column (1), multiplied by the average number of industries per county with VC deals, represents a 33% increase in deals off the 1970 base of 0.93 deals per university county, per standard deviation increase in the innovation index. Meanwhile, the coefficient in column (3) represents an increase of 57% in unique local investors off the 1970 base of 1.27 deals per university county.

These estimates assume that more and less treated county-industries were on similar VC growth trajectories before the innovation shock occurred in 1980 with the passage of the Bayh Dole Act. Figure 4 supports the validity of this assumption. It 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 indistinguishable from zero and on a flat trend before 1980, demonstrating that the parallel trends assumption holds.

We perform a number of analyses to assess the robustness of our findings. First, our main results utilize a sample of the top 100 innovating universities. We find that the results are nearly identical if we instead expand our sample to include the top 200 most innovating universities (Appendix Table XX). Second, our main results assume the university "treats" only the county in

which it is contained. For robustness we re-run our analyses with an alternative dataset in which we count as treated all counties within 75 miles of a sample research university. While the coefficients are, unsurprisingly, somewhat smaller, since outcomes are measured on average further away from universities, the results remain qualitatively similar and statistically significant under this alternative treatment classification (Appendix Table XXX). The fact that these estimates are smaller further supports the importance of local knowledge spillovers—as university-related corporate innovation increases 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.

4.2. 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. Those local areas would also see the largest associated increases in local corporate innovation, as corporations move to the university area to take advantage of its ideas, and as start-ups enter. We evaluate this mechanism by employing variation in the amount of federal research funding received by universities in the years prior to Bayh-Dole.

We first show, descriptively, that VC growth was greater in counties whose universities received more federal funding before 1980. Figure 5 plots average county VC levels for the top and bottom federal funding deciles of counties containing our top 100 universities. For each outcome—number of deals (Panel (a)), number of investors (Panel (b)), and VC funds invested (Panels (c) and (d)), the top and bottom decile counties look quite similar until Bayh Dole, at which point they diverge, and the top decile counties receive more VC.

We test the federal funding mechanism more formally using a variation on our central identification strategy, which compares more versus less affected industries in the same county, after the law passage relative to before. 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 (2020a) 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 5 presents estimates of this model with outcomes of VC funds invested (column (1), $mil.), log of one plus VC funds invested (column (2)), number of deals (column (3)), and number of unique active investors (column (4)). The estimates are consistent with 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 four 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. Figure 6 illustrates this effect graphically, plotting coefficients on triple interaction terms between the innovation index, ex ante federal funding, and year, such that the curve represents the evolution of treatment effects over time. The magnitudes reflect the magnification of the between-industry VC growth differences for higher versus lower innovation index industries within a county. While the industry gaps in more and less funded counties are relatively similar before 1980, they open up thereafter, supporting the role of federal funding and thus the Bayh Dole Act.

4.3. University Innovation Shock? Or Corporate Innovation Stock?

The passage of Bayh Dole coincided with other regulatory changes that affected the amount of capital available for VCs to invest. 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, which meant that VCs suddenly had considerably more capital to deploy than in prior years. Was the increase in funding to university counties and related industries after 1980, shown above, simply due to this general increase in VC funding? 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. But because the 1979 ERISA change was so significant to the VC industry, we turn next to thinking about where these new VC funds would have been invested in the absence of a university innovation shock, and to testing these alternative hypotheses directly.

Presumably, if the effects we document are simply the result of increased VC funding, we should see this increase in funding occur across the board, not just in university counties. We have shown in Table 2, however, that funds increase disproportionately in university counties. Universities may be highly innovative areas generally, though, and one expects VC to be found in innovative areas. An alternative to the university innovation shock hypothesis could be that university counties and related industries simply had disproportionate shares of pre-1980 corporate innovation output, and that this corporate activity is what drew VC dollars when they became available due to ERISA. In other words, we might expect to see VC funds flowing to areas with significant pre-1980 innovation output, regardless of the presence of a university. The maps in Figure 1 suggest that corporate innovation was much more geographically pervasive prior to 1980 than was university innovation (Panels (a) and (b)). The industry distribution of established corporate innovation may also have differed somewhat from those affected by university innovation. To formally test our alternative hypothesis, we use the full geographic and industry distribution of pre-1980 corporate innovation as a measure of the counterfactual destinations for VC funding after ERISA in the absence of the university innovation shock: VC dollars would have gone to the locations and industries where corporate innovation was strongest.

To implement the test, 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 indeces in the same regression, asking which type of innovation better predicts differential VC outcomes after 1980: established corporate innovation, or university innovation, which likely represents the frontier. We then estimate the following model:

$$(4)\ VC_{cit} = \beta_0 + \beta_1(I(year > 1980) * univ_index_{ci}) + \beta_2(I(year > 1980) * corp_index_{ci}) + \vartheta_{it} + \varphi_{ct} + \theta_{ci} + \epsilon_{cit},$$

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; 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 is meant to control for nationwide growth in VC in certain industries, unrelated to university innovation, while the county X year fixed effects absorb any unrelated cross-industry shocks over time in a given location. County X industry fixed effects account for location-specific industry strengths that are consistent over time. $univ_index_{ci}$ is the standardized Hausman (2020a) university innovation index for county *c* in industry *i* and $corp_index_{ci}$ is the standardized corporate innovation index for county *c* in industry *i*. Because both measures are standardized, their coefficients are directly comparable. Due to the fixed effects structure, both innovation indices' main effects are absorbed, as is the indicator for post-1980. Standard errors are clustered at the county level.

The results of the estimation are presented in Figure 7 and Table 5. The points in the figure represent coefficients on $univ_index_{ci}$ X year dummy and $corp_index_{ci}$ X year dummy interaction terms in a fully expanded version of Equation (4), such that they reflect treatment effects of ex-ante university versus corporate innovation on VC outcomes. Figure 7 indicates that, regardless of which VC funding measure we use, VC funding flows after Bayh Dole (1980) 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 corporate innovation.[14] 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 VC funding. In contrast, the estimates show little support for the competing story that overall increased VC funding availability led to increased flows into counties with high stocks of established (pre-1980) corporate innovation output. This well-identified result confirms the intuition provided by the maps in Figure 2, which suggest visually, using geographic variation only, that the locations of VC growth in the 1980s most closely resemble the locations of university innovation before 1980.

Another alternative hypothesis also arises. It is possible 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. (Recall 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, following the approach in Kortum and Lerner (2000) of scaling VC by contemporary corporate R&D expenditures to control for known innovation opportunities, and this time using the full industry *and* geographic variation. We then estimate a similar model to those in Equation (4) and Table 5, adding a VC index interaction term in addition to those for university and corporate innovation.

Table 6 present estimates of variations on the model:

$$(5)\ VC_{cit} = \beta_0 + \beta_1(I(year > 1980) * univ_index_{ci}) + \beta_2(I(year > 1980) * corp_index_{ci}) + \beta_3(I(year > 1979) * VC_index_{ci}) + \vartheta_{it} + \varphi_{ct} + \theta_{ci} + \epsilon_{cit},$$

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

[14] 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 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. 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 (2020a) university innovation index for the county-industry; $corp_index_{ci}$ is the standardized corporate innovation index for the county-industry; and 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.

Panel A of Table 6 presents estimates from models where the outcome variable is the total dollar VC investment in the county-industry-year, while Panel B presents estimates from models where the outcome variable is log one plus the total VC investment. Regardless of how the LHS variable is specified, we observe a similar pattern: even controlling for the county-industry specific stocks of pre-980 corporate innovation and pre-1979 VC investment activity, we observe a positive and significant effect post-Bayh Dole on VC in precisely the counties and industries in which the local universities were most research-productive. As in the prior models, we observe a small and insignificant effect of prior stock of corporate innovation on VC flows post- vs. pre- Bayh Dole. While the volume of pre-1979 VC investment activity does have a positive association with post-1979 VC investment funding flows (Panel B, columns (3) and (4)), this association does not affect the statistical significance or magnitude of the estimates on the interaction between post-1980 and the university innovation index (Panel B, columns (5) and (6)). The evidence suggests that the university innovation shock from Bayh-Dole leads specifically to disproportionate flow of VC investment activities to the affected industries in university counties. Meanwhile, the positive and significant coefficients on the VC Index X Post-1979 interaction terms in columns (5) and (6) support Kortum and Lerner (2000)'s assumption that VC to some extent did expand in existing investment areas after ERISA.

4.4. 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, VC also surely stimulates further innovative activity. This second direction of causality is a necessary component of the "virtuous cycle" of innovation

and capital that successful entrepreneurial clusters have, and other places lack. To test the extent to which VC generates corporate innovation, we employ the same test described by Equation (5), but we replace the VC outcomes on the left hand side with corporate citation-weighted patenting outcomes. Do pre-ERISA allocations of VC across geographic areas and industries predict the county-industries of post-ERISA corporate innovation?

Table 7 presents the results. Panel A uses the citation-weighted number of corporate patents, while Panel B uses the natural logarithm of one plus citation weighted corporate patents. Columns (3) and (4) of both panels in indicate that when the VC Dollar Index and the VC Investor Index are each included alone, VC does indeed predict corporate innovation, as in Kortum and Lerner (2000). When the university and corporate innovation indices are added to the regression, however, the university index remains positive and significant while the coefficients on the VC indeces become indistinguishable from zero. This evidence suggests that pre-ERISA VC generates later corporate innovation only to the extent that it flows after Bayh-Dole and ERISA to university related geographical areas and industries. University innovation generates increased corporate innovation nearby in related industries, and the VC it attracts is surely a key input to this process. Meanwhile, there is a substantial ramping up of corporate innovation in areas in which it was already established before 1980, but much of it is unrelated to universities and does not eliminate the clear university effect.

The estimates illustrate the virtuous cycle that exists between innovation in capital. A shock to university innovation draws VC funding and investors to the regions, who in turn fund further innovative activity, as shown by Kortum and Lerner (2000). Kickstarting the cycle, however, is the shock to university innovative output, which serves to draw the increased capital flows from the ERISA changes to the region. Once we control for the existing stock of corporate innovation and the shock to university innovation output, however, VC dollars on their own do not exhibit a significant relationship to future innovation. Put differently, without innovation activity to provide opportunities for investment of funds, VC availability in a region (say, through a government fund, etc.) 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 of innovation attracting VC funding that in turns 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).

4.5. Long Term Outcomes: High Growth Entrepreneurship

Our final set of tests examines the longer-term association between university counties, federal research funding, and high growth entrepreneurial activity. We run 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 XX estimates models of the form:

$$(6)\ IDE_{ct} = \beta_0 + \beta_1 I(university_county)_c + \vartheta_t + \epsilon_{ct},$$

while Panel B estimates models of the form:

$$(6)\ IDE_{ct} = \beta_0 + \beta_1 avg_Fed_Fund_c + \vartheta_t + \epsilon_{ct},$$

where 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: being a university county at the time of Bay Dole's passage and the amount of federal funding awarded to the university in the pre-Bayh Dole period are both strongly associated with eventual higher long run levels of high growth entrepreneurial entry. More specifically, in all four specifications, for both the university county indicator and the average federal funding measure, we observe a positive and significant coefficient. <<marginal effects here >>.

While these estimates represent correlations, and are not identified, they are suggestive, and consistent with the overall hypothesis that a shock to innovative activity ignites a virtuous cycle of capital investing in innovation and leading to future production of innovation, leading to emergence of high growth entrepreneurship clusters.

<<vcs picking right stuff here, Table 9>>.

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 a number of important policy implications:

1. Release innovation into the wild
2. You need the innovation to produce good targets for VC investment
    a. As a result, may be better to spend $$ on programs to encourage innovation and commercialization rather than on programs to create venture funds
    b. 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.

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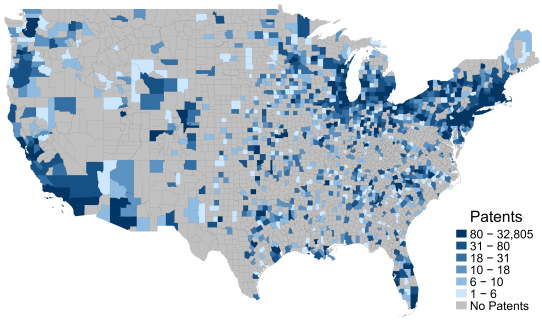
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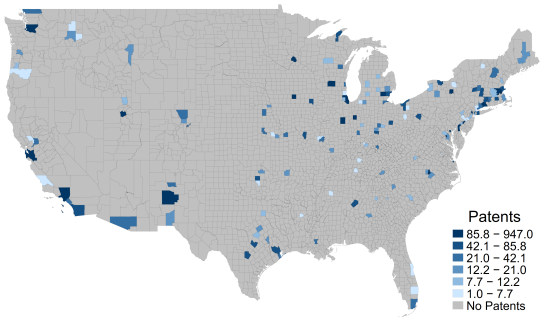
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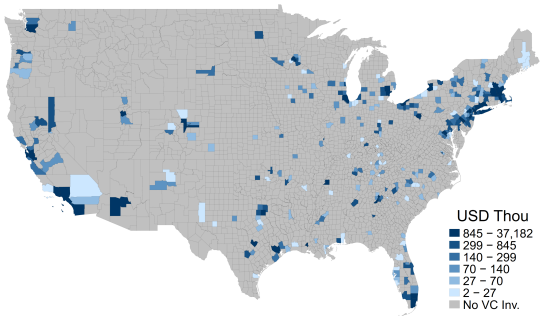
Figure 1: The Geography of Innovation and Venture Capital



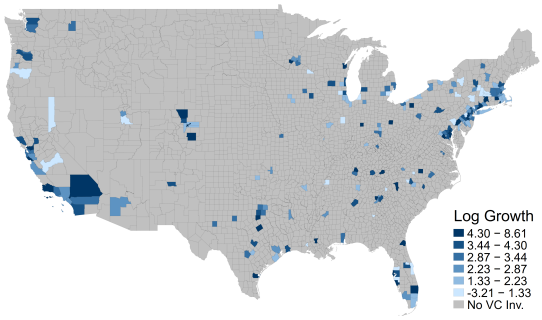
(a) Corporate Innovation, 1976-1980



(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 university and corporate 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, 1976-1995

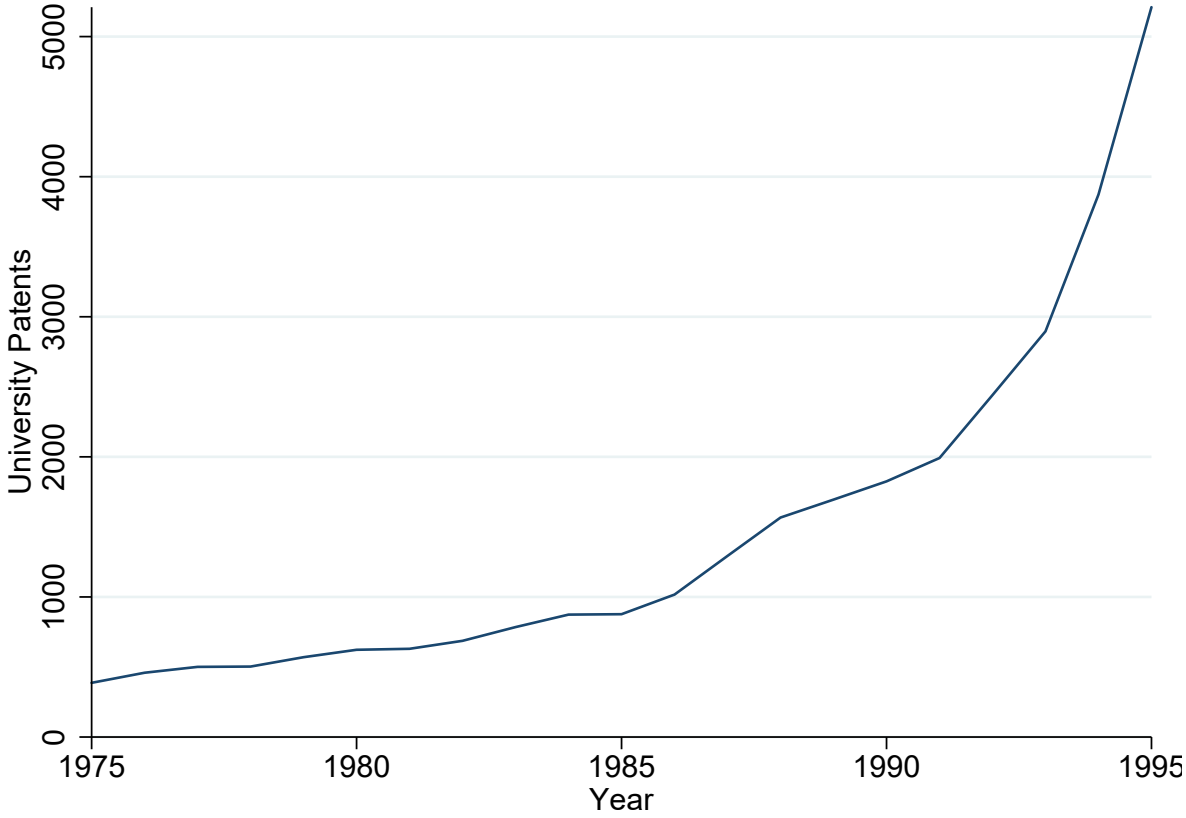
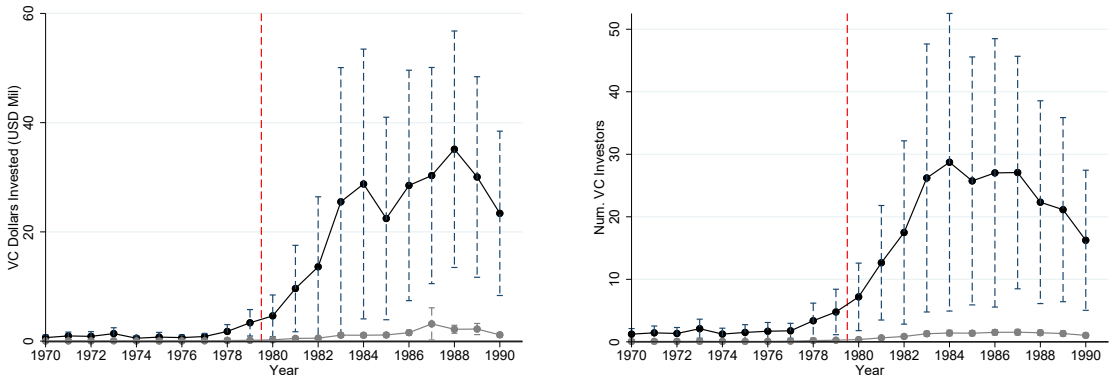


Figure 3: VC in University and Non-University Counties

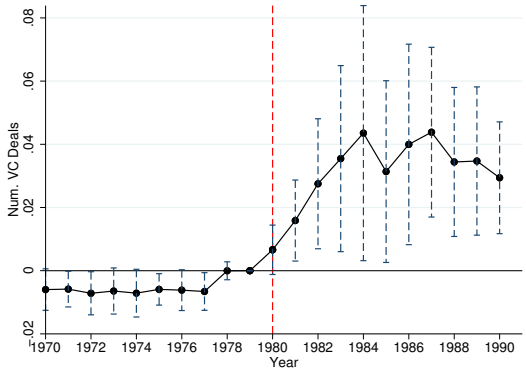


(a) VC Dollars Invested (mil.)

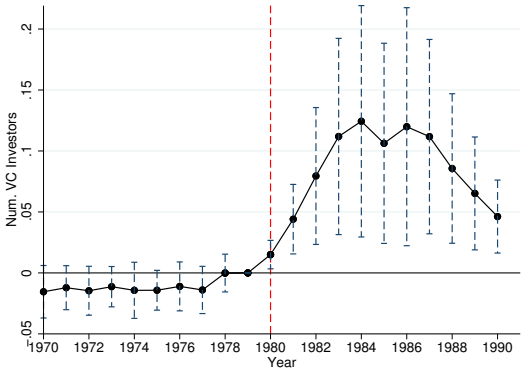
(b) Num. Investors

Notes: [dark curve is university (containing) counties, gray curve is non-university counties. Data points represent raw means of outcome]

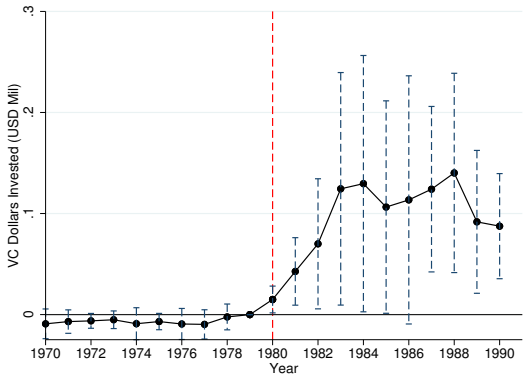
Figure 4: University Innovation Effects on Venture Capital Outcomes



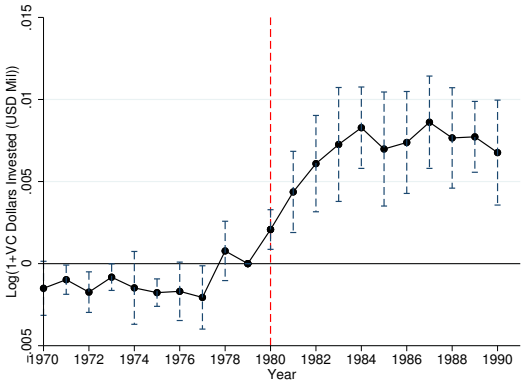
(a) Num. Deals



(b) Num. Investors



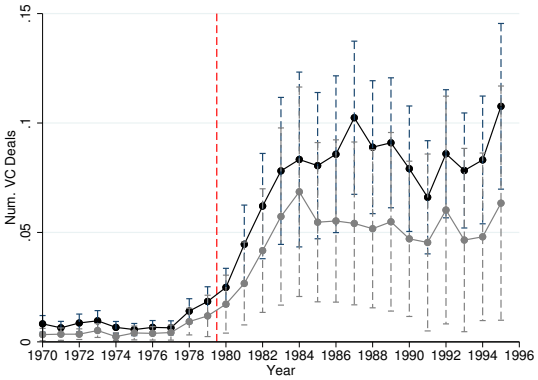
(c) VC Dollars Invested (mil.)



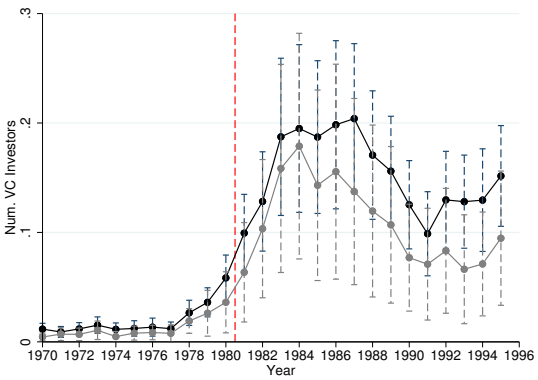
(d) Log(1+VC Dollars Invested (mil.))

Notes: [Points represent treatment effects of ex-ante university innovation affecting a particular county-industry on the VC outcome indicated. All regressions control for the corporate innovation index. All regressions include fixed effects for county-industry, county-year, and industry-year. Error bars indicate 95% confidence intervals.]

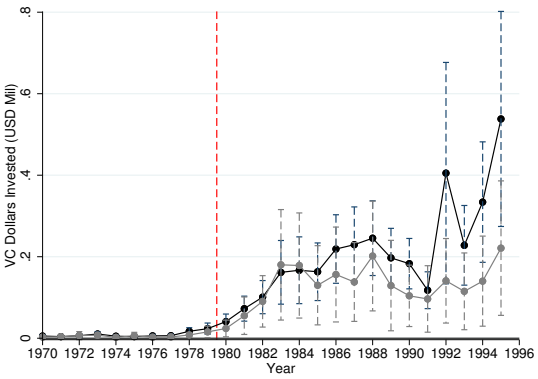
Figure 5: Top vs. Bottom Decile Federally Funded Counties



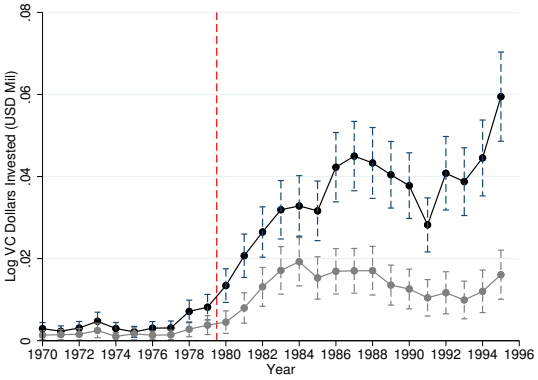
(a) Num. Deals



(b) Num. Investors



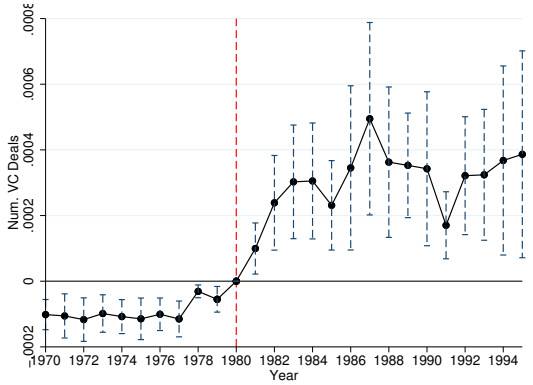
(c) VC Dollars Invested (mil.)



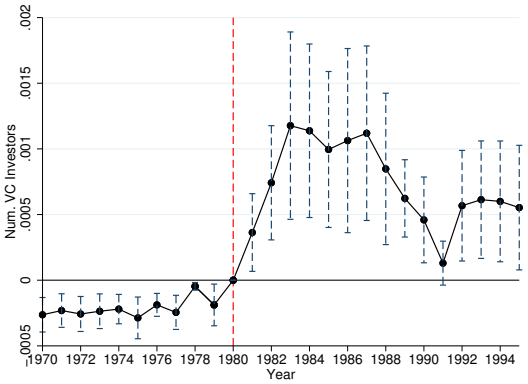
(d) Log(1+VC Dollars Invested (mil.))

Notes: [dark curve is top decile of counties in terms of federal research funding, gray curve is bottom decile. Data points represent raw means of outcome]

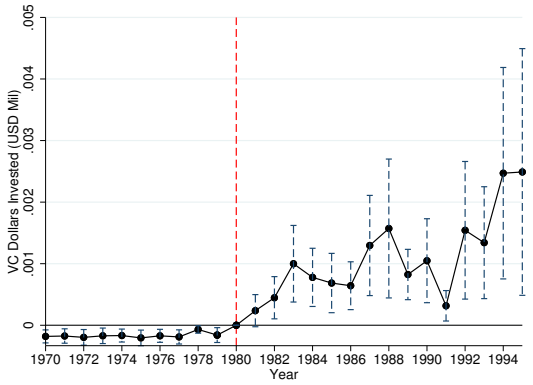
Figure 6: Marginal Impact of Federal Research Funding on University Innovation Effects



(a) Num. Deals



(b) Num. Investors



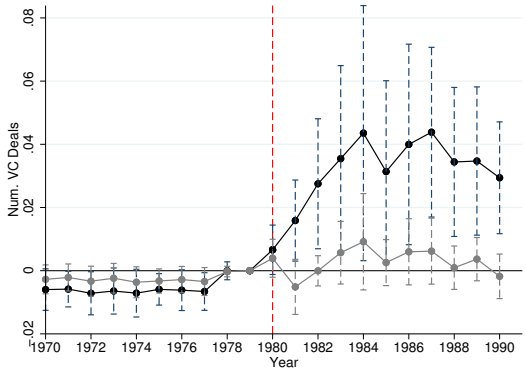
(c) VC Dollars Invested (mil.)



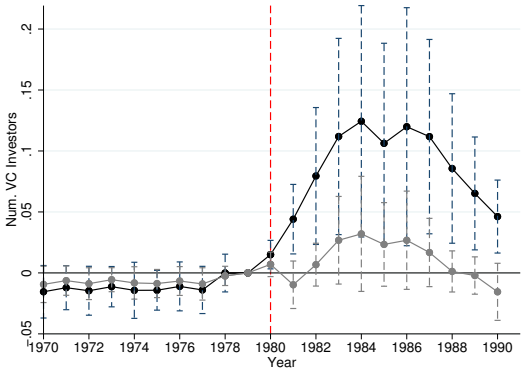
(d) Log(1+VC Dollars Invested (mil.))

Notes: [Points represent the marginal treatment effect of ex-ante university innovation in a county with more ex-ante federal research funding allocated to the local universities. Points are treatment coefficients on the triple interaction of innovation index X total federal funding X year. All regressions include fixed effects for county-industry, county-year, and industry-year. Error bars indicate 95% confidence intervals.]

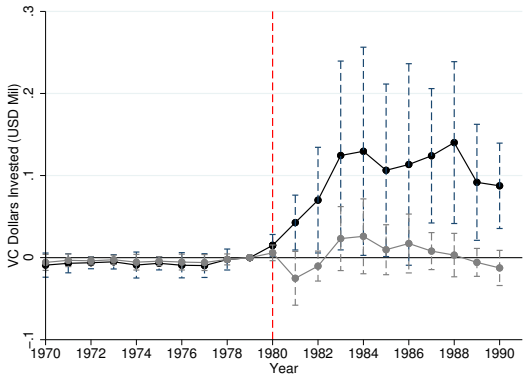
Figure 7: University and Corporate Innovation Effects on Venture Capital Outcomes



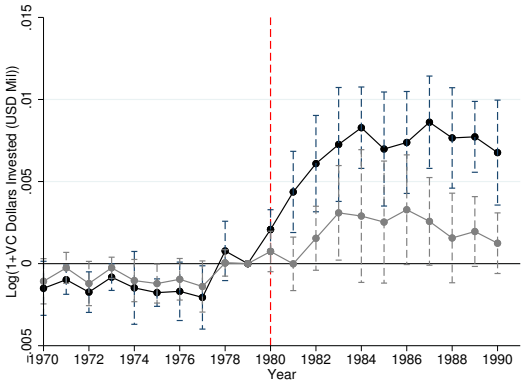
(a) Num. Deals



(b) Num. Investors



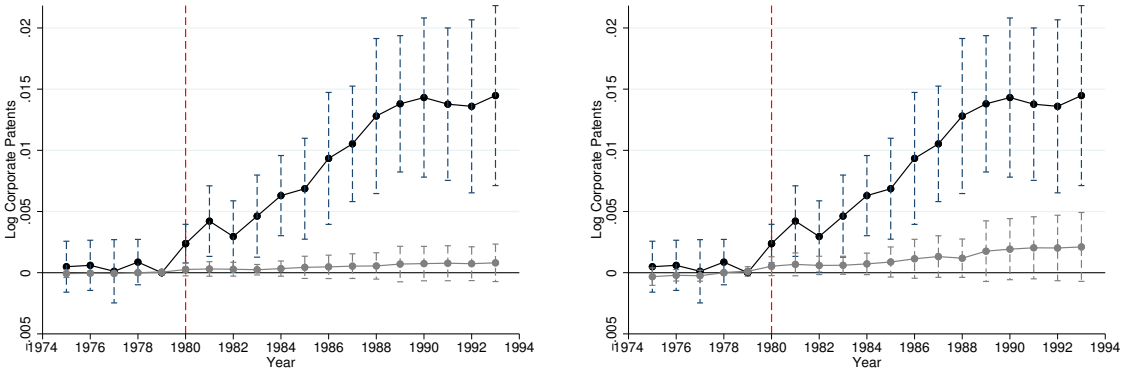
(c) VC Dollars Invested (mil.)



(d) Log(1+VC Dollars Invested (mil.))

Notes: [Points on the dark curve represent treatment effects of ex-ante university innovation affecting a particular county-industry on the VC outcome indicated. Points on the gray curve represent treatment effects of ex-ante corporate innovation affecting a particular county-industry on the VC outcome indicated. All university effect regressions control for the corporate innovation index and vice versa. All regressions include fixed effects for county-industry, county-year, and industry-year. Error bars indicate 95% confidence intervals.]

Figure 8: University and Ex-Ante VC Effects on Corporate Patenting



(a) VC Dollar Index

(b) VC Investor Index

Notes: [Points on the dark curve represent treatment effects of ex-ante university innovation affecting a particular county-industry on log one plus corporate patents. Points on the gray curve represent treatment effects of ex-ante VC in a particular county-industry on log one plus corporate patents. All university effect regressions control for the VC index and vice versa. All regressions include fixed effects for county-industry, county-year, and industry-year. Error bars indicate 95% confidence intervals. Note that panel (a) is scaled by R&D and the right panel is not. I also have a version of the right panel that's scaled by corporate R&D and looks more similar to the left panel.]

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, 1990	75	24.02	68.15	0.00	467.20
Avg. Base Funds (1/2 x (1970+1990))	75	12.34	35.10	0.00	241.03
Funds Diff, 1990-1970	75	23.36	66.11	0.00	452.34
County VC Deals, 1970	75	0.93	2.95	0.00	18.00
County VC Deals, 1990	75	10.20	31.19	0.00	218.00
Avg. Base Deals (1/2 x (1970+1990))	75	5.57	16.98	0.00	118.00
Deals Diff, 1990-1970	75	9.27	28.45	0.00	200.00
County VC Investors, 1970	75	1.27	4.03	0.00	24.00
County VC Investors, 1990	75	16.68	50.76	0.00	358.00
Avg. Base Investors (1/2 x (1970+1990))	75	8.97	27.22	0.00	191.00
Investors Diff, 1990-1970	75	15.41	47.14	0.00	334.00

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

	VC Funds ($mil.) (1)	Log VC Funds (2)	Deals (3)	Investors (4)	Corp. Patents (5)	Log Corp. Patents (6)
$I^{Yr\geq 1980}\times$ Univ. County	0.062***	0.009***	0.021***	0.041**	3.848***	0.129***
	(0.022)	(0.002)	(0.008)	(0.016)	(1.177)	(0.017)
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
N	17,779,923	17,779,923	17,779,923	17,779,923	17,779,923	17,779,923
R-Sq	0.088	0.267	0.533	0.495	0.550	0.792

Notes: An observation in the sample is a county-industry-year for the years 1970-1995. Regressions predict total VC dollars (mil.) invested 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.) The dependent variable in columns (2) and (6) are the logs of one plus the variable indicated. 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: VC Funds

Dependent Variable:	VC Dollars Invested ($Mil)			
	(1) Level	(2) Level	(3) Level	(4) Log
$I^{Yr \geq 1980}\times$ Univ. Innov. Index	0.118**	0.106**		0.008***
	(0.047)	(0.048)		(0.002)
$I^{Yr \geq 1980}\times$ Univ. Cit-Wt Innov. Index			0.054**	
			(0.021)	
Industry-Year FE	Yes	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes
N	14,314,457	8,704,079	14,314,457	14,314,457
Window	1970-1995	1975-1990	1970-1995	1970-1995
R-Sq	0.093	0.076	0.093	0.287

Panel B: VC Deals and Investors

Dependent Variable:	Num. Deals		Num. Investors	
	(1)	(2)	(3)	(4)
$I^{Yr \geq 1980}\times$ Univ. Innov. Index	0.037**	0.036**	0.087**	0.095**
	(0.015)	(0.014)	(0.034)	(0.038)
Industry-Year FE	Yes	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes
N	14,314,457	8,704,079	14,314,457	8,704,079
Window	1970-1995	1975-1990	1970-1995	1975-1990
R-Sq	0.554	0.628	0.527	0.592

Notes: An observation in the sample is a county-industry-year for the years 1970-1995 (unless otherwise indicated). Regressions in Panel A predict total VC dollars (mil.) invested in a county-industry-year and include fixed effects for county-year, industry-year, and county-industry in addition to the regressors shown. Regressions in Panel B predict number of VC deals or number of unique VC investors in a county-industry-year and include the same fixed effects. 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 in Panel A, row 2 is the raw version of the standardized index in row 1. Panel A, Column (3) includes a non-standardized measure of the university innovation index. Standard errors are clustered by county. * indicates significance at the 10% level, ** at 5%, and ***at 1%.

Table 4: Marginal Impact of Federal Research Funding on University-VC Effect

	Funds ($Mil.) (1)	Log(1+Funds) (2)	Deals (3)	Investors (4)
Avg. Annual Fed Funding × $I^{Yr\geq 1980}$× Univ. Innov. Index	0.0013*** (0.000)	0.0001*** (0.0000)	0.0004*** (0.0001)	0.0009*** (0.0003)
$I^{Yr\geq 1980}$× Univ. Innov. Index	0.022 (0.014)	0.003*** (0.001)	0.007 (0.004)	0.017* (0.010)
Industry-Year FE	Yes	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes
N	17,672,239	17,672,239	17,672,239	17,672,239
R-Sq	0.092	0.286	0.545	0.512

Notes: An observation in the sample is a county-industry-year for the years 1970-1995. Regressions predict total VC dollars (mil.) invested in a county-industry-year (col. (1)), log one plus VC dollars invested (col. (2)), number of VC deals (col. (3)), and number of VC investors (col. (4)), 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 **??** of the text. Standard errors are clustered by county. * indicates significance at the 10% level, ** at 5%, and ***at 1%.

Table 5: University Innovation, Corporate Innovation, and VC Outcomes

Dependent Variable:	(1) Funds ($Mil.)	(2) Log(1+Funds)	(3) Deals	(4) Investors
$I^{Yr \geq 1980} \times$ Univ. Innov. Index	0.117**	0.008***	0.037**	0.085**
	(0.046)	(0.002)	(0.014)	(0.034)
$I^{Yr \geq 1980} \times$ Corp. Innov. Index	0.002	0.002	0.002	0.006
	(0.011)	(0.001)	(0.003)	(0.009)
Industry-Year FE	Yes	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes
N	14,314,457	14,314,457	14,314,457	14,314,457
Window	1970-1995	1970-1995	1970-1995	1970-1995
R-Sq	0.093	0.287	0.554	0.527

Notes: An observation in the sample is a county-industry-year for the years 1970-1995 (unless otherwise indicated). Regressions predict VC dollars invested, log one plus VC dollars invested, number of VC deals, and number of VC investors 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 indeces are 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 6: Predictors of Post-ERISA VC Investment

Panel A: VC Funds Invested (Levels, $Mil.)

	Dependent Variable: VC Funds Invested ($Mil)					
	(1)	(2)	(3)	(4)	(5)	(6)
$I^{Yr\geq 1980}$ × Univ. Innov. Index	0.118**				0.115**	0.113**
	(0.047)				(0.047)	(0.047)
$I^{Yr\geq 1980}$ × Corp. Innov. Index		0.053			0.002	0.003
		(0.037)			(0.011)	(0.010)
$I^{Yr\geq 1979}$ × VC Dollar Index			0.037		0.029	
			(0.031)		(0.022)	
$I^{Yr\geq 1979}$ × VC Investor Index				0.059		0.049
				(0.040)		(0.031)
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
N	13,957,071	11,271,974	13,957,071	13,957,071	13,957,071	13,957,071
Window	1970-1995	1970-1995	1970-1995	1970-1995	1970-1995	1970-1995
R-Sq	0.100	0.061	0.095	0.096	0.100	0.101

Panel B: Log(1+VC Funds Invested $Mil.)

	Dependent Variable: Log(1+VC Funds Invested ($Mil))					
	(1)	(2)	(3)	(4)	(5)	(6)
$I^{Yr\geq 1980}$ × Univ. Innov. Index	0.008***				0.008***	0.007***
	(0.002)				(0.002)	(0.002)
$I^{Yr\geq 1980}$ × Corp. Innov. Index		0.006**			0.002*	0.002*
		(0.003)			(0.001)	(0.001)
$I^{Yr\geq 1979}$ × VC Dollar Index			0.003**		0.003***	
			(0.002)		(0.001)	
$I^{Yr\geq 1979}$ × VC Investor Index				0.005**		0.004**
				(0.002)		(0.002)
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
N	13,957,071	11,271,974	13,957,071	13,957,071	13,957,071	13,957,071
R-Sq	0.292	0.284	0.283	0.285	0.293	0.294

Notes: An observation in the sample is a county-industry-year for the years 1970-1995 (unless otherwise indicated). Regressions predict VC dollars (mil.) invested 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 indeces are constructed from pre-1980 innovation, as described in Section 3 of the text. The VC indeces are constructed from pre-1979 VC investor and investment locations, as described in Section **??** of the text. * indicates significance at the 10% level, ** at 5%, and ***at 1%.

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

Panel A: Citation-Weighted Corporate Patents

	Dependent Variable: Citation-Weighted Corporate Patents					
	(1)	(2)	(3)	(4)	(5)	(6)
$I^{Yr\geq 1980}$ × Univ. Innov. Index	6.660**				4.576*	4.572*
	(2.774)				(2.686)	(2.686)
$I^{Yr\geq 1980}$ × Corp. Innov. Index		8.626***			6.824*	6.823*
		(3.877)			(3.546)	(3.547)
$I^{Yr\geq 1979}$ × VC Dollar Index			0.255***		–0.137	
			(0.088)		(0.131)	
$I^{Yr\geq 1979}$ × VC Investor Index				0.303**		–0.056
				(0.149)		(0.117)
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
N	13,957,071	13,957,071	13,957,071	13,957,071	13,957,071	13,957,071
R-Sq	0.601	0.611	0.568	0.568	0.625	0.625

Panel B: Log(1+Citation-Weighted Corporate Patents)

	Dependent Variable: Log(1+Citation-Weighted Corporate Patents)					
	(1)	(2)	(3)	(4)	(5)	(6)
$I^{Yr\geq 1980}$ × Univ. Innov. Index	0.021***				0.011***	0.011***
	(0.004)				(0.004)	(0.004)
$I^{Yr\geq 1980}$ × Corp. Innov. Index		0.036***			0.032**	0.032**
		(0.013)			(0.012)	(0.012)
$I^{Yr\geq 1979}$ × VC Dollar Index			0.001**		–0.000	
			(0.001)		(0.000)	
$I^{Yr\geq 1979}$ × VC Investor Index				0.002*		0.000
				(0.001)		(0.001)
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
N	13,957,071	13,957,071	13,957,071	13,957,071	13,957,071	13,957,071
R-Sq	0.829	0.830	0.828	0.828	0.830	0.830

Notes: An observation in the sample is a county-industry-year for the years 1970-1995. Regressions predict citation-weighted corporate patents (Panel A) and the log of one plus citation-weighted corporate patents (Panel B) 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 indeces are constructed from pre-1980 innovation, as described in Section **??** of the text. The VC indeces are constructed from pre-1979 VC investor and investment locations, as described in Section **??** of the text. * 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

	Entrants with Eventual Growth Events (1)	Quality-adj. Quantity of Entrep. Entrants (2)	Entrant Quality Index (3)	Realized-to-Exp Eventual Growth Events (4)
University County	2.693***	1.253***	0.000***	0.776***
	(0.854)	(0.301)	(0.000)	(0.267)
Year FE	Yes	Yes	Yes	Yes
N	22,038	22,038	22,038	22,038
R-Sq	0.078	0.122	0.002	–0.000

Panel B: By Federal Research Funding

	Entrants with Eventual Growth Events (1)	Quality-adj. Quantity of Entrep. Entrants (2)	Entrant Quality Index (3)	Realized-to-Exp Eventual Growth Events (4)
Avg. Annual Federal Research Funding	0.056***	0.025***	0.000***	0.011***
	(0.019)	(0.007)	(0.000)	(0.004)
Year FE	Yes	Yes	Yes	Yes
N	22,038	22,038	22,038	22,038
R-Sq	0.162	0.243	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)-(3) and actual-to-expected eventual growth events in columns (4)-(6). All outcomes are future-measured events of current year new business registrants. Regressions include year fixed effects. The university and corporate innovation indeces are constructed from pre-1980 innovation, as described in Section **??** of the text. VC dollars invested are measured contemporanously 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

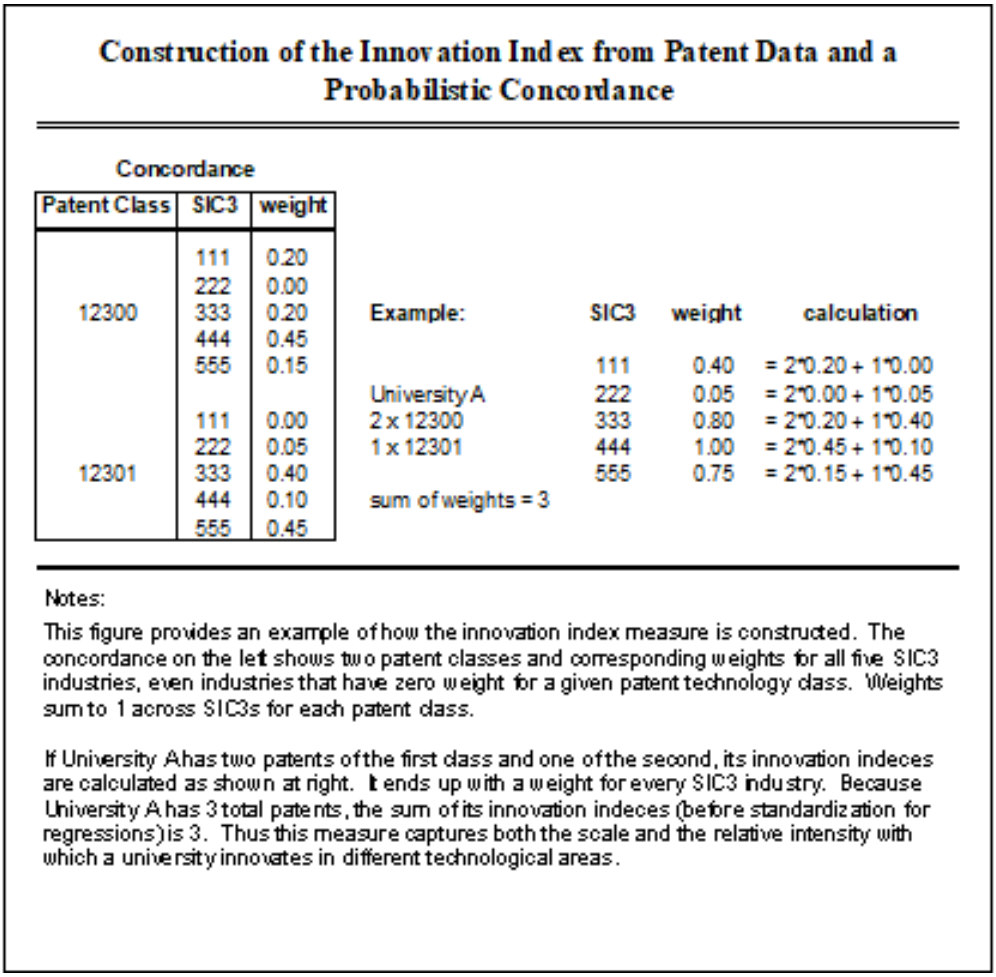
	Entrants with Eventual Growth Events			Realized-to-Expected Eventual Growth Events		
	(1)	(2)	(3)	(4)	(5)	(6)
Univ. Innov Index	0.734***	0.652**	0.220*	0.139***	0.127**	–0.005
	(0.271)	(0.263)	(0.122)	(0.052)	(0.052)	(0.022)
Corp. Innov Index		0.213	–0.125***		0.031	–0.061***
		(0.155)	(0.034)		(0.032)	(0.016)
VC Dollars Invested ($Mil)			0.038***			0.013***
			(0.009)			(0.002)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	22,038	22,038	21,968	22,038	22,038	21,968
R-Sq	0.352	0.375	0.671	0.000	0.000	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 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 indeces are constructed from pre-1980 innovation, as described in Section **??** of the text. VC dollars invested are measured contemporanously with the entrepreneurial entry outcomes. * indicates significance at the 10% level, ** at 5%, and ***at 1%.

Appendix for Online Publication

A Appendix Tables and Figures

Figure A1: Illustrative Example: Construction of the Innovation Index



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

Concordance

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

Example:

University A
2 x 12300
1 x 12301

sum of weights = 3

SIC3	weight	calculation
111	0.40	= 2*0.20 + 1*0.00
222	0.05	= 2*0.00 + 1*0.05
333	0.80	= 2*0.20 + 1*0.40
444	1.00	= 2*0.45 + 1*0.10
555	0.75	= 2*0.15 + 1*0.45

Notes:

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

If University A has two patents of the first class and one of the second, its innovation 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.