The Geographic Reach of Market and Non–Market Channels of University Research Commercialization

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Work in Progress: Comments Welcome

Abstract

This paper compares the geographic "reach" of knowledge flows from university inventions through two important channels: market contracts (licenses) and non–market "spillovers" exemplified by patent citations. We find that knowledge flows through market transactions to be more geographically localized than those operating through non–market spillovers. Moreover, the differential effects of distance on licenses and citations are most pronounced for exclusively licensed university patents. We interpret these findings as reflecting the incomplete nature of licensing contracts and the need for licensees to maintain access to inventor know–how for many university inventions. Such access appears to be less important for inventions that are non–exclusively licensed (e.g. "research tools").

JEL Classifications: O31, O32, R12

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1 Introduction

A substantial body of recent research has examined the contributions of university research to regional economic development and technological innovation (Jaffe 1989; Jaffe, Trajtenberg, and Henderson 1993; Acs, Audretsch, and Feldman 1992, 1994; Audretsch and Stephan 1996; Zucker, Darby, and Armstrong 1998; Agrawal 2000; Adams 2001). Interest in this topic has been sparked by the extensive historical and anecdotal evidence of links between U.S. university research and the growth of high–technology industries such as semiconductors, computer software, and biotechnology. The growth of these high-technology clusters in the United States suggests the presence of strong regional agglomeration effects that reflect proximity to universities or other research institutions. Accordingly, much of the literature on the economic contributions of university research has focused on the extent to which these contributions are localized.

This literature suggests that the channels through which university-based research affects regional economic or innovative activity may be divided into two broad categories: knowledge "spillovers" (i.e., positive externalities from university research that affect the performance of nearby firms) and "market-based" channels such as technology licensing or various types of employment relationships between academic scientists and firms. Most of this empirical research suggests that the economic or innovative contributions of university-based research tend to be geographically concentrated, but little or no empirical research has yet compared the geographic incidence of these market and nonmarket channels of interaction. This paper undertakes such an analysis, comparing the localization of outflows of university-based research through citations to university patents and through licenses that involve these same patents.

We conduct this analysis at the regional level, disaggregate among broad technological areas, and control for inter-regional differences in industrial composition and population. Our empirical analysis contains important limitations, however. The data are drawn from a small set of research universities that may not be representative of all U.S. universities. In addition, our comparative analysis of knowledge flows in patent citations and licensing agreements excludes other potential channels of interaction. Nevertheless, the opportunity to consider multiple avenues of technology transfer for the same set of inventions allows us to address questions that thus far have been overlooked in the literature.

A finding that the geographic "reach" of knowledge spillovers differs from those of market-based channels would have significant implications for industrial managers and university administrators. Managerial decisions on the location of R&D and other knowledge-intensive activities often are influenced by beliefs about the characteristics of the channels through which academic knowledge is transferred to industrial practice. And for university administrators, especially those in public universities, the renewed concern of federal and state policymakers with the level of economic returns from university-based research is matched only by these policymakers' concerns with the national and regional distribution of these returns.

Immediately below, we consider the reasons for the observed localization of the effects of university research and discuss some of the prior literature on geographic localization. This section is followed by an explanation of our data sources and methodology. Section 4 presents and discusses our empirical findings, and Section 5 concludes the paper.

2 Why Are the Effects of University Research Localized?

The extensive literature on technology management and the economics of innovation argues that virtually all technologies contain important "tacit" elements such as aspects of know-how, performance, operations, etc., that cannot be easily codified in a blueprint, a published article, or a contractual document. Oral communication of tacit knowledge over long distances may be ineffective or infeasible. As a result, technology transfer is frequently described as a "contact sport," in which the transfer or exchange of personnel is essential. The limited geographic reach of such channels for the exchange of information and know-how is widely cited as one of the leading causes of regional agglomeration economies. Marshall (1896) pointed out in his celebrated discussion of this topic that in such areas, "the mysteries of the industry are in the air," and therefore presumably more accessible to local participants or would-be entrants.

Despite the enormous outpouring of literature on "industrial districts" and regional high-technology complexes such as Silicon Valley in Northern California or Route 128 in Massachusetts, the mechanisms that create and sustain these regional concentrations are not well understood. Knowledge "spillovers," which are widely believed to be important to these localized economic and innovative effects, are defined by economists to be "externalities," for which the source of the spillover is not fully compensated. For example, technical knowledge acquired through the trade press or by participation in industry conferences constitutes a knowledge spillover. In other words, pure knowledge "spillovers" operate through non-market mechanisms. But many other channels for technology transfer that sustain regional concentrations of industry are market-based. For example, the extensive regional high-technology infrastructures in the Boston or San Francisco areas of lawyers, venture capitalists, consultants, equipment suppliers, and the like all operate within markets for labor, services, and information. At the same time, however, contracts for new or complex technologies frequently are incomplete, markets for such technologies are often thin and subject to "small-numbers" problems, and contracts rarely can codify all knowledge necessary for the exploitation of the technology (Arrow 1962, Williamson 1975, Mowery 1983). There are strong reasons to suspect that these and other factors limit the geographic reach of market mechanisms for the transfer of embryonic technologies.

The literature on universities' regional economic effects also reaches a mixed verdict on the relative importance of market and non-market-based channels in the realization of these effects. Jaffe, Trajtenberg and Henderson (1993) examine the extent to which "spillovers" of university-based research are locally concentrated using citations to university patents to measure spillovers. These scholars measure the localization of these spillovers by examining the relative proportions of university patents and a "control sample" of patents from the same years and technology classes that are cited by inventors in the same state and in the same "standard metropolitan statistical area" (SMSA).[1] They find significant localization effects; inventors of patents that cite university patents are more likely to be in the same state or SMSA than are inventors that cite patents from their control sample. No attempt is made to compare the strength of localization effects by tech-

[1] The "control sample" of patents provides a means of controlling for regional variations in industry composition, since the citation of patents in the same year and technology class as those from local universities is (other things equal) likely to reflect local industrial concentration.

nological area, although Jaffe, Trajtenberg, and Henderson do note that these localization effects are similar for patent citations that span patent classes and those within patent classes. Although their analysis excludes self-citations, their data do not enable Jaffe, Trajtenberg, and Henderson to control for the potential existence of market relationships (e.g., licenses) between firms citing university patents and the universities or inventors whose patents are cited. To the extent that these market relationships exist, these scholars' findings of localization may reflect the operation of market and non-market channels of knowledge transfer, rather than a pure knowledge spillover.

Indeed, recent research by Lynne Zucker and Michael Darby and their co-authors (Zucker, Darby, and Armstrong 1998; and Zucker, Darby, and Brewer 1999) suggests that a significant fraction of knowledge transfer between universities and biotechnology firms can be attributed to market-mediated interactions between a relatively small number of "star" university-based scientists and biotechnology firms.[2] Rather than spillovers, Zucker and colleagues argue that knowledge flows from universities to industry through these "star" academic scientists' industrial roles as principals, consultants, employees, or members of scientific advisory boards. Their analysis shows that co-authorship between industry scientists and academic "stars" has a significant and positive effect on the number of new products being developed by biotechnology firms. Related (less robust) results suggest that knowledge transfer between university scientists and firms is enhanced further by contractual affiliations between the scientists and the firms in the sample. These results suggest that the geographic "knowledge networks" that link academic researchers and industrial innovators operate largely through market channels.

Zucker and Darby's results contrast with those of Audretsch and Stephan (1996), who examined interactions between university-based scientists and firms based on disclosures in biotechnology firms' initial public offering (IPO) documents about academic researchers' roles in the firms. Audretsch and Stephan find that "approximately 70 percent of the links between biotechnology companies and university–based scientists are non-local" (p. 649), and conclude that "While proximity matters in establishing formal ties between university-based scientists and companies, the influence is anything but overwhelming" (p. 650). The Audretsch–Stephan results introduce yet another interpretation of the channels of interaction between universities and industry. Like Zucker and Darby, Audretsch and Stephan argue that university-industry knowledge interactions operate primarily through market channels. But Audretsch and Stephan find that proximity is not essential to the operation of these markets:

> "...geographic proximity matters when knowledge spillovers are informal. But an important conclusion of this paper is that when knowledge is transmitted through formal ties between researchers and firms, geographic proximity is not necessary, since face to face contact does not occur by chance but instead is carefully planned." (p. 651)

[2]Zucker, Darby, Armstrong, and Brewer define "star" scientists as those active researchers at the "leading edge" of basic science research. In biotechnology, they identified 327 scientists worldwide who reported at least 40 genetic sequencing discoveries in the Genebank database or published a minimum of 20 genetic sequencing discoveries.

Agrawal (2000) examines the role of geography in university-industry interaction for a sample of 124 electrical, mechanical, and software technologies licensed from the Massachusetts Institute of Technology (MIT). Although geographic proximity is positively associated with the likelihood and extent of product commercial success (measured by probability of product introduction and level of licensing royalties) for these technologies, this significant effect vanishes when Agrawal controls for the intensity of university researchers' involvement with the licensee.[3] It is apparent from the analysis that for many university-invented technologies, which are often at an early stage of development, inventor interaction is important. Geographic localization effects may still be important, however—the sample in the Agrawal study is selected from licensed technologies only, and these technologies may be licensed by nearby firms because of the ability to interact with university researchers that geographic proximity may afford.[4]

Taken together, the findings of these four studies suggest that geographic proximity to university research is important not only for non-market spillovers, but also for market channels of interaction and knowledge exchange.[5] But none of these studies directly compares localization of market and non-market channels of technology transfer for the same set of inventions. That issue is the focus of our empirical investigation.

3 Data and Methods

The primary sources of data for our empirical analysis are the technology transfer offices at Columbia University, the University of California, the University of Michigan, and Stanford University. According to a recent licensing survey by the Association of University Technology Managers (AUTM 2000), California, Columbia, and Stanford were among the top five recipients of gross licensing income from patent licenses among U.S. universities in fiscal year 1999 ($96 million, $81 million, and $40 million, respectively).

[3]Zucker, Darby, and Armstrong, and Brewer operationalized firm-scientist interaction as article co–authorship and Audretch and Stephan categorized scientist roles from information in IPO documents. Agrawal measures the intensity of interaction between university researchers and licensees as the number of hours that university researchers devote to direct collaboration with the licensee firm to solve technical and development problems after the invention is licensed from MIT, but before revenues are generated. Interestingly, although the licensing agreement represents a market-based instrument for interaction, interaction between the firm and university researchers may or may not be governed by contractual agreements. For example, some MIT faculty may maintain consulting, employment, or founding relationships with the firms in Agrawal's sample of licensees. Likewise, involvement by graduate student researchers with licensee firms may occur through employment or thesis research. Nevertheless, it is clear from the analysis that collaboration with MIT researchers aided the commercial success of licensees, no matter how these collaborations were organized.

[4]In a survey of sixty–two university technology transfer offices, Jensen and Thursby (2001) found that 48% of licensed technologies were at only the "proof of concept" stage of development, and that for an additional 29% only a lab-scale prototype existed at time of licensing. These findings suggest that many licensed university technologies are characterized by substantial uncertainty and require sizeable development efforts. In light of these characteristics of the university inventions, it is not surprising that personal interaction between researcher and firm often is necessary for commercial success.

[5]Recent studies of federal research labs (Jaffe, Fogarty, and Banks 1998) and the semiconductor industry (Podolny and Shepard 1996 and Almeida and Kogut 1999) suggest that non-market spillovers are geographically mediated in these settings as well.

The University of California has been a licensor of faculty-invented technology since at least the 1950s, while Stanford established its Office of Technology Licensing (OTL) in 1970. Columbia established its technology transfer office in 1981, shortly after passage of the Bayh-Dole Act, which simplified the process by which universities could retain and license intellectual property resulting from federally funded research. Our sample includes inventions from the Stanford and Columbia campuses, all nine University of California campuses (Berkeley, Davis, Irvine, Los Angeles, Riverside, San Diego, San Francisco, Santa Barbara, and Santa Cruz), and the Ann Arbor campus of the University of Michigan, or twelve inventing locations in all.[6]

Internal records at these four university technology transfer offices contain a wealth of information on the inventions of faculty, students, and research staff. University policies require that researchers "disclose" new inventions through a formal invention disclosure document. "Invention disclosures" from these universities enable one to trace (1) whether a patent application was filed in the U.S. and other industrial economies; (2) whether a patent was issued for the invention; (3) whether the patent was licensed to private firms, the general terms (e.g., exclusive or nonexclusive) of the license, and the identity and location of the licensee; and (4) the amount if any of license fees and royalties for each license. The University of California data cover more than 10,000 invention reports dating back to the 1950s, the Columbia University data contain information on 1,600 inventions disclosed since 1981, and the University of Michigan and Stanford University data contain over 3,000 invention disclosures each.

Our analysis compares the extent of localization of two channels through which university inventions may affect innovative firms or individuals: (1) a non-market medium represented by citations to university patents in the patent applications filed by these firms or individuals, and (2) a market mechanism represented by licensing agreements of various types. Locational information associated with each of these avenues enables us to identify the extent of localization of each channel for technology outflow.

Much previous work on the regional effects of academic research has employed a variant of the "knowledge production function" developed by Griliches (1979). In Jaffe, Trajtenberg, and Henderson (1993), patterns of localization are analyzed for a sample of academic patents and a "control population" of non-cited patents of similar vintage and industrial classification. This general procedure is less well-suited to the concerns of this paper, however, which seeks to compare the regional patterns of citations to academic patents with the regional distribution of licenses for these patents. A control population of patents can be constructed, but there is no obvious control population for licenses. Instead, we use the U.S. Census Bureau's Metropolitan Statistical Area data to formulate two dependent variables: (1) the number of patents from a given campus that are linked to that metropolitan area through citations to those patents, and (2) the number of licenses to entities in that region from that campus for the same patented inventions. We base these dependent variables on patents issued during 1975–88; for each patent, we include only citations or licenses during the 8 years following the patent's issue.

In addition to analyzing the entire sample of licensed and cited patents, we separately

[6] The Merced campus of the University of California was established too late to be included in this sample.

consider patents that are licensed exclusively and nonexclusively. We also disaggregate our analysis by technological "area," producing a campus–technology–region "triple" as our unit of analysis. Our dependent variables represent the "intensity" of licensing or citing activity to campus i's patents in technology area j (defined below), accounted for by geographic region k (defined below). We further disaggregate our licenses and citations in the year following the university patent's issuance to capture licensing and citing trends over time.[7]

Patent citations have been used in previous studies as measures of technological knowledge "spillovers," i.e., the use of knowledge by an inventor of the work of a previous inventor where no contractual agreement is necessary and where in many cases no compensation is paid. When the US Patent and Trademark Office (USPTO) grants a patent, the granting officer includes a list of all previous patents on which the granted patent is based. This list is made public as part of the publication of the patent at the time it issues. The patent officer is aided in compiling a list of previous patents by the patent applicant, who is legally bound to provide with the application a list of all patents that constitute relevant "prior art."[8] Citations of prior patents thus serve as an indicator of the technological lineage of new patents, much as bibliographic citations indicate the intellectual lineage of academic research.

Our use of licenses and patent citations as indicators of market and non-market technology transfer introduces an interesting measurement issue. A license clearly signifies a market transaction between licensor and licensee, but a patent citation may not indicate a knowledge spillover. For example, a patent attorney or patent examiner at the USPTO may add citations during the patent application process. If the inventor were not aware of such prior art, these citations would overstate the level of non–market knowledge spillover. Jaffe, Fogarty, and Banks (1998) found that up to one–third of all citations to patents issued to a sample of patents assigned to the National Aeronautics and Space Administration appeared not to represent knowledge spillovers. Similarly, a survey of patent holders by Jaffe, Trajtenberg, and Fogarty (2000) suggests that up to one-half of all citations may not constitute spillovers. Nevertheless, the authors of these two studies conclude that patent citations, while "noisy," are valid measures of knowledge spillovers.[9]

Citations to patents typically peak in applications filed 4–5 years after the date of issue of the cited patent. As a result, data on citations to patents issued during 1975–96 will be "right–truncated," i.e., more recent patents will be underrepresented in the citations data. For this reason, we examined citations to patents issued during 1975–1988 (for these four universities, a total of 840 patents), and for each year's cohort of patents, analyzed only citations made in applications appearing during the 8 years following that year. Since

[7]Although we consider licensing and citing activity for eight years after each university patent's issue date, we add a category for licenses or citations occurring before the patent issue date (negative lag).

[8]In addition to the legal requirement, it is in the applicant's interest to be forthcoming in this list because a more complete description of prior art is likely to reduce the prospects of an interference being declared during processing of a patent application.

[9]To the extent that the likelihood that a citation does not represent a non-market spillover is related to the distance between the inventors of the citing and cited patents, our citation equation results could be biased. But Jaffe, Fogarty, and Banks (1998) and Jaffe, Trajtenberg, and Fogarty (2000) find no evidence of such bias in their analyses of citations and spillovers.

our geographic analysis is limited to the United States, we exclude citations made by patents that list only inventors in non–US locations. In order to make our patent citation and licensing samples as comparable as possible, we also exclude citations by those entities that are not likely to be licensees: universities, non-profit foundations, non-profit hospitals, and governmental agencies (although we include citations by patents jointly assigned to a university or governmental agency and a private firm or individual).[10] Similarly, we exclude patents that are not cited by another US patent *and* licensed in the US. Table 5 presents the total numbers of patents, licenses, and citations generated by the California, Columbia, Michigan, and Stanford sub–samples, and the number of patents, licenses, and citations that remain after these exclusions.

*** Table 5 Here ***

<u>*Geographic Regions and Distance:*</u> We employ the Metropolitan Statistical Areas (MSAs) used by the US Census Bureau to define economically distinct geographic regions in the United States. MSAs are defined to be an "integrated economic and social unit with a large population nucleus." MSAs with a population of at least 1 million are disaggregated into sub–units called Primary Metropolitan Statistical Areas (PMSA). PMSAs in these regions combine to form a Consolidated Metropolitan Statistical Area (CMSA).[11] In 1990, the Census Bureau defined 18 CMSAs and 258 MSAs in the United States. In this paper we consider only CMSAs and MSAs, and restrict our analysis to the largest fifty regions, based on "manufacturing value–added" attributed to each region in the 1987 Economic Census. Table 2 lists these geographic areas, their share of total US manufacturing value–added, and their shares of sample licenses and patent citations.[12]

*** Table 2 Here ***

We obtained the zipcodes for each university campus and for the central business district for the largest city of each of the 51 metropolitan regions in our analysis. For each of the campus$_i$–CMSA/MSA$_k$ pairs in our analysis, we computed distance as the number of miles between their respective zipcodes, DISTANCE$_{i,k}$. We also included a variable for the square of distance, in order to capture non–linearity in the distance relationship to licensing or citing activity. In cases where multiple inventors were listed in the citing patent, we used the city and state location of the first listed inventor.[13]

[10] We include citations to university patents made by three "foundations:" The Battelle Institute, The Gas Research Institute, and the Electric Power Research Institute. These three foundations, while nominally non-profit, have large industrial clienteles and therefore could conceivably represent potential licensees.

[11] For example, the San Francisco CMSA is composed of seven PMSAs: San Francisco and San Mateo Counties, Santa Clara County, Santa Cruz County, Alameda and Contra Costa Counties, Marin County, Solano and Napa Counties, and Sonoma County. In contrast, the San Diego region constitutes one MSA. Four of our eleven campuses are located within the San Francisco CMSA (Stanford University and the University of California campuses at Berkeley, San Francisco, and Santa Cruz). One of our campuses is located within the San Diego MSA (University of California at San Diego).

[12] Although the level of manufacturing value–added generated by the Sacramento MSA places this region outside the top 50, because this MSA is home to the University of California, Davis campus, we include Sacramento to expand the list to 51 regions in our analysis.

[13] In cases where both foreign and U.S. inventors were listed, we use the location of the first listed U.S. inventor.

Population:

We control for the substantial differences among our regions in size and economic "pull" with the log of the population count for each CMSA/MSA$_k$ from the 1990 census, LNPOP$_k$.

Technology Classification: Patents are classified by the US Patent and Trademark Office into "fields of invention" at the time of issue. Unfortunately, the USPTO fields of invention are not compatible with the structure of the SIC system. We therefore employ a concordance developed by Silverman (1996) to aggregate the sample patents into three-digit Standard Industrial Classifications (SICs), and report results for the 24 three–digit SICs accounting for the majority of patents in our sample.[14] This concordance produces produces the counts of licenses and citations generated by each SIC$_j$–CMSA/MSA$_k$ pair that we use as the dependent variables in our analysis.[15]

Other Controls: Differences in the importance of patents as a means for appropriating the returns to invention in different technology fields affect the probability that inventors are scanning patented "prior art" assiduously and influence the importance of formal licensing agreements for the exploitation of university inventions. Where patent protection is of great importance, patent citations are likely to be a more reliable guide to intellectual antecedents of patented invention and licensing agreements are likely to be economically significant. We utilize data from the original Yale Survey of Technological Opportunity and Appropriability (Levin, Klevorick, Nelson, and Winter 1987), which represents the assessment by senior industrial R&D managers (*circa* 1983) of the importance of formal instruments of intellectual property protection for capturing the returns to industrial innovation in their 3–digit SIC. Several questions in the survey address the issue of the ability of patents to enable the innovator to appropriate the returns to innovation. Our measure of the importance of formal patent protection uses the mean scores on a seven–point Likert scale for responses to the following question (I.B.1): *"In this line of business, how effective are patents in preventing competitors from duplicating an improved product?"* Survey responses are reported at the four–digit SIC level. Since our analysis is conducted at the 3–digit SIC level, we aggregate the responses for each four–digit SIC sub–level to its "parent" three–digit level, weighting each four–digit mean response by its corresponding manufacturing value–added from the 1987 Census of Manufactures.[16]

We also include indicator variables for the top five SICs that account for the bulk of our licensing activity: SIC 283 (drugs), 366 (communications equipment), 367 (electronic components), 382 (measuring and controlling devices), and 384 (medical instruments). Fi-

[14]For a patent assigned by the USPTO to a particular international patent class (IPC), the Silverman concordance calculates the likelihood that this patent would be employed in a particular "SIC of use" and assigns weights to each SIC equal to its likelihood. For a detailed description of the construction and validity of this concordance, see Silverman 2002. The concordance files are available at http://www.rotman.utoronto.ca∼silverman/ipcsic/documentation_IPC-SIC_concordance.htm.

[15]Because the Silverman concordance probabilistically disaggregates a patent appearing in a particular patent class into multiple SICs, summed counts generated by this concordance will not necessarily be integer values.

[16]The Yale survey does not cover three of the SICs included in this study (SICs 239, 307, and 385). We identified observations represented by these SICs by the indicator variable, NOTINYALE.

nally, we include indicator variables identifying Columbia patents, Michigan patents and Stanford patents (with University of California patents as the left–out category). Table 3 summarizes the definitions and notation for our variables.

*** Table 3 Here ***

Our university patents are contained in 9 2–digit SICs: 23 (textiles), 28 (chemical products), 30 (rubber), 32 (stone, clay, and glass products), 34 (fabricated metal products), 35 (non–electrical industrial equipment), 36 (electrical and electronic equipment), 38 (scientific and measurement instruments), and 39 (miscellaneous manufacturing industries). Our CMSA/MSA sample accounts for 59% of total US manufacturing value-added, 81% of all citations within 8 years of our sample patents, and 93% of all licenses within 8 years (Table 2).

The potential number of observations in each of our specifications equals the number of campuses (12) times the number of selected SICs (24) times the number of selected CMSA/MSAs (51) times the number of possible citing or licensing years (9),[17] yielding a possible 132,192 observations. But this maximum is reduced by several factors. First, although the University of California campuses of Santa Barbara and Santa Cruz produced patents that were licensed and cited during the 1975–96 time period, none of these campuses' patents are cited by industrial firms, nor are they licensed by industrial firms on an exclusive or non–exclusive basis. We therefore exclude these campuses from the analysis. The UC Riverside campus reports no exclusively licensed patents that are cited, and the UC Irvine campus data contain no non–exclusively licensed patents that are cited; these campuses also were excluded from the appropriate regressions.

The structure of the resulting pooled dataset consists of 12,240 observations and 110,160 observations for the panel data set for our analyses of overall licensing and citing activity. The subsample of citations and licensing agreements for exclusively and non-exclusively licensed patents is 11,016 observations for the pooled data and 99,144 observations when we disaggregate our sample into a panel (due to the exclusion of UC Riverside and UC Irvine, respectively). Table 4 displays the descriptive statistics for the primary independent variables for the overall (pooled) patent sample, the subset of exclusively licensed patents, and the subset of nonexclusively licensed patents.

*** Table 4 Here ***

Our empirical strategy is to conduct separate regressions for licensing and citing activity and compare the magnitude and direction of the corresponding coefficients in those equations. The regression specifications for licenses and citations accordingly contain the same set of observations, corresponding to the number of campuses, regions, and industries in the sample. The independent variables in each of these equations are also identical. The dependent variables measure licensing or citing activity and are described more fully in Table 3. We construct similar variables for the exclusively licensed and non-exclusively licensed patent sub-samples.

[17] As mentioned earlier, we include year variables for years 1–8 plus an indicator for instances where the citation or license occurred before the university patent's issue date.

The analysis is complicated by several factors. First, we are unable to observe much of the substantial heterogeneity among regions and among industries located within each region. For example, transportation costs between regions and campuses may depend on the location of airline hubs (a factor that affects flight schedules and travel time) and airfares between cities. The presence of venture capital that could facilitate the commercialization of university technology varies by region. The presence of other research universities from which a firm may license or cite patents also varies by region, and is unrelated to distance from our campuses. Moreover, different types of industrial facilities (e.g., manufacturing plants, design centers, and headquarters offices) may be concentrated in different regions. In order to account for our ignorance of many of these differences, we use random–effects regression equations with SIC_j–$\mathrm{CMSA/MSA}_k$ (industry–region) specific effects. We also control for the left truncation at zero of our dependent variables and account for the count nature of our dependent variables by using a conditional maximum likelihood poisson model (Wooldridge 1999).[18]

We first report the results of regressions for all licensed and cited patents in our sample, then separately report results for licenses covering exclusively and nonexclusively licensed patents and the citations to the patents associated with each type of agreement. We compare the results of specifications for the geographic distribution of citations to patents that are licensed exclusively with those for the geographic distribution of the licensees signing exclusive licensing agreements, and compare citations to patents that are licensed on a nonexclusive basis with the geographic distribution of nonexclusive licensees. Separating licensed patents by type enables us to analyze the effects of distance on several different forms of market transactions and compare these with the effects of distance on spillovers associated with the same set of inventions.

The licensing and citation specifications measure the impact of geographic localization on different dependent variables. Therefore, we cannot directly compare coefficients between these two sets of regressions. Instead, we convert our coefficient estimates to "standardized" or "beta" coefficients and use these coefficients as a basis for comparison.[19] A representative standardized coefficient and its standard error are shown below:

$$\hat{\beta}^*_x = \frac{s_x}{s_y}\hat{\beta}_x \tag{1}$$

$$s_{\hat{\beta}^*_x} = \frac{s_x}{s_y} s_{\hat{\beta}_x} \tag{2}$$

Since standardized coefficients are normalized and free of scale, we can use these coefficients to compare the relative influence of corresponding independent variables in the

[18]Our derived "counts" of licenses and citations are not uniformly integers. Wooldridge points out that in the conditional maximum–likelihood poisson model, the dependent variable need not represent integer counts, however (Wooldridge 1999, p. 81).

[19]A standardized coefficient is generated by multiplying the coefficient estimate for a regressor X by its standard deviation and dividing by the standard deviation of the dependent variable Y. Since the original coefficient is a slope, multiplying by the ratio of the standard deviations removes both the units of Y and X. Such a variable can thus be interpreted as measuring the effect (in standard deviations) on the dependent variable by a one standard deviation change in the value of the independent variable, enabling direct comparison of the influence of different independent variables on a dependent variable.

licensing and citation equations on their respective dependent variables (number of licenses or citations). Thus, we can contrast the influence of the same independent variable on different channels of technology transfer. To determine whether these effects are significantly different, we test the null hypothesis that the licensing and citation standardized coefficients are equal:

$$H_O : \hat{\beta}^*_{xL} - \hat{\beta}^*_{xC} = 0 \tag{3}$$

$$H_A : \hat{\beta}^*_{xL} - \hat{\beta}^*_{xC} \neq 0 \tag{4}$$

using the following derived test statistic:[20]

$$Z = \frac{\hat{\beta}^*_{xL} - \hat{\beta}^*_{xC}}{\sqrt{VAR(\hat{\beta}^*_{xL}) + VAR(\hat{\beta}^*_{xC}) + 2 \times COV(\hat{\beta}^*_{xL}, \hat{\beta}^*_{xC})}} \tag{5}$$

and conducting a two–tailed test assuming that Z is distributed normally.

4 Results and Discussion

A comparison of the proportions of patent citations and license agreements accounted for by leading CMSA/MSAs (Table 2) suggests that the market–mediated licensing agreements are somewhat more "localized" than the knowledge spillovers captured through patent citations. Column 3 in Table 2, corresponding to the number of citations among regions to our sample of patents, shows that almost all of the 50 leading regions plus Sacramento are home to citers of our university patents (the lone exception being the Lancaster, PA MSA). Column 6 reports the incidence of licensing among these regions and indicates that licensing activity is more concentrated—only 26 of the 51 regions are locations of licensees of the patents in our sample, and these regions tend to be those with the largest manufacturing value–added.

These regional statistics nonetheless mask considerable interindustry variation. Moreover, the aggregate data for both patent citations and license agreements display a strong bicoastal pattern: New York, Boston, San Francisco, and Los Angeles account for significant shares of both citations and license agreements, while Chicago, Houston, Minneapolis, and other large metropolitan areas distant from the coasts account for much smaller numbers of licenses and citations. This pattern of exploitation of inventions from our four universities complicates a simple "distance-decay" interpretation of university economic

[20] The denominator in equation 5 is the standard deviation (square root of the variance) of the combined licensing and citation standardized coefficients in the random effects models and can be expressed in terms of the underlying coefficients using the basic definition of the variance of two jointly distributed variables: $\left(\frac{S_{xL}}{S_{yL}}\right)^2 VAR(\hat{\beta}_{xL}) + \left(\frac{S_{xC}}{S_{yC}}\right)^2 VAR(\hat{\beta}_{xC}) + 2 \times \left(\frac{S_{xL}}{S_{yL}}\right) \times \left(\frac{S_{xC}}{S_{yC}}\right) \times COV(\hat{\beta}_{xL}, \hat{\beta}_{xC})$. ($S_{xL}$, S_{xC}, S_{yL}, and S_{yC} are conditional on the sample and are assumed to be constants in this calculation.) The covariance term accounts for the correlation between corresponding variables in these equations. We estimate the covariance of the underlying coefficients, $COV(\hat{\beta}_{xL}, \hat{\beta}_{xC})$, by regressing the licensing and citation equations jointly using the "seemingly unrelated regression" (SUR) technique (Zellner 1962).

effects. We expect the indicator variables CALIFORNIA and NORTHEAST to account for the bicoastal patterns present in the data.

Table 5 contains the results of our poisson analysis of the entire sample of university patents, Table 6 and Table 7 respectively contain results for exclusively licensed and nonexclusively licensed patent sub–samples. In each table, the first four models consider the effects of the independent variables on the number of licenses accounted for by each observation, and the last four models consider the effects of these same variables on the number of citations to the same set of patents. In each table, the basic specification (L1 and C1) reports the influence of population and patent importance on licensing and citing activity. We then add measures for distance and the square of distance in equations L2 and C2. The third set of equations (L3 and C3) controls for university differences by including indicator variables for Columbia, Michigan, and Stanford observations. Finally, the fourth set of equations (L4 and C4) adds additional controls for technology by including indicator variables for the five leading SICs in our sample (SICs 283, 366, 367, 382, and 384).

Table 8 contains standardized coefficients that are analogous to the coefficients for $LNPOP_k$, $PATIMP_j$, and $DISTANCE_{i,k}$ in the licensing and citation specifications in which we add distance measures to the basic controls (models L2 and C2 in Tables 5, 6, and 7). Table 8 also reports the results of our tests of the hypothesis that the standardized coefficients generated from the licensing and citation equations are equal (columns 3 and 4 of Table 8). We turn first to the results for the overall patent sample (Table 5).

*** Table 5 Here ***

The coefficients for the regional population, $LNPOP_k$, are positive and significant for all eight specifications. This result is not surprising, as we expect more populous regions to more intensively license or cite university inventions, *ceteris paribus*. When we consider the licensing standardized coefficients for $LNPOP_k$ in Table 8, however, we see that population affects licensing more than citations. This difference in the standardized coefficients for $LNPOP_k$ is consistent with the patterns exhibited in Table 2 that licenses tend to be more concentrated among the larger metropolitan areas, while citations are distributed more evenly among all sizes of regions in our sample. The difference between the standardized coefficients is only weakly significant, however (10%).

The coefficient for $PATIMP_j$ is also positive and significant in equations 5L1–5L3, suggesting that licensing contracts are more important in accessing university inventions for the technology classes in which patent protection is judged to be an important mechanism for appropriating the returns to innovation. But differences among technologies in the importance of patents as mechanisms for capturing the returns to invention should have a smaller effect on citation than on licensing, a hypothesis that is supported by the ratio of the standardized coefficients for licensing and citations in Column 5 in Table 8. This ratio for $PATIMP_j$ is -1.4, suggesting that patent appropriability influences licensing activity to a greater extent than it influences citing activity, consistent with our expectation [21]

[21] The standardized coefficients in Table 8 are derived from the full licensing and citation models (models L4 and C4 in Tables 5, 6, and 7. For the overall sample, the coefficient for $PATIMP$ is negative in C4,

In equations 5L2 and 5C2, we introduce the variables of particular interest in our analysis, the distance variables $DIST_{i,k}$ and $DISTSQ_{i,k}$. In these and subsequent equations, $DIST_{i,k}$ is consistently negative and significant, while $DISTSQ_{i,k}$ is positive and significant. The negative coefficients on $DIST_{i,k}$ suggest that greater distance is associated with lower licensing or citing activity. Conversely, the positive coefficients for $DISTSQ_{i,k}$ indicate that beyond some distance from our universities, licensing and citation begin to increase again, revealing an upwardly concave relationship between distance and the share of citations or agreements accounted for by a given CMSA/MSA–SIC pair.

The $DIST_{i,k}$ coefficients for patent citations (equations 5C2–5C4) are smaller than for licensing agreements (equations 5L2–5L4), indicating that citation-based "spillovers" decline less sharply as distance from the patent–holding university increases than does the market-based channel of licensing. Moreover, the difference between the corresponding standardized coefficients for licensing and citations (column 4 of Table 8) is highly significant. Table 8 provides further evidence that distance affects licensing activity more heavily than it does citations. The ratio of the standardized coefficients for distance in the licensing and citations equations exceeds two (column 5), suggesting that this decline is twice as rapid for licensing. The Z–statistic of -2.81 also suggests that distance has a stronger effect on licensing than on citation activity, and they support the argument that the incomplete nature of licensing contracts limits the ability of more distant firms to exploit such advances, contradicting the conclusions of Audretsch and Stephan (1996).The variables identifying Columbia, Michigan, and Stanford patents, $COLUMBIA$, $MICHIGAN$, and $STANFORD$, are inserted in equations 5L3 and 5C3 to control for differences among our four universities. The positive and significant coefficients indicate that patents issued to Stanford and Columbia are more intensively licensed and cited than are University of California patents. In contrast, the coefficients for $MICHIGAN$ are not significant, suggesting that there is little difference in the intensity of licensing or citing of University of Michigan patents and University of California patents in our sample. Equations 5L4 and 5C4 also control for industry effects associated with the five largest industries in the sample. The insertion of indicator variables to control for campus and 3-digit SIC effects does not greatly change the coefficient estimates for $LNPOP_k$, $PATIMP_j$, $DIST_{i,k}$, and $DISTSQ_{i,k}$, although the significance of the coefficients for most of these variables suggests the presence of strong industry-specific and university-specific effects.

Table 5 reports the results of two tests of the validity of each model. The Wald statistic tests the null hypotheses that all coefficients in each model are jointly equal to zero. The positive and significant Wald statistics allow us to reject this hypothesis for all eight models. We also report the results of the likelihood-ratio test of $\alpha = 0$, which compares the panel estimator with the pooled estimator. The positive and significant test results for each model supports the use of the panel estimator.

Table 6 reports results for the subsample of exclusively licensed patents.

*** Table 6 Here ***

These results are broadly similar to those reported for the overall sample of patents. $DIST_{i,k}$ is negative and significant and $DISTSQ_{i,k}$ is positive and significant in licensing

producing the negative standardized coefficient ratio. In equations C1–C3 in 5, the coefficients are positive however, although still much smaller than the corresponding coefficients in equations L1–L3.

models 6L2–6L4 and citation models 6C2–6C4. The hypothesis test results in Table 8 (column 3) indicate that distance has a significantly greater effect on licensing than on citation to these exclusively licensed patents as well. The $DIST_{i,k}$ standardized coefficient ratio in Table 8 for the sub–sample of exclusively licensed patents is greater than the corresponding ratio for the overall sample, however ($\frac{\hat{\beta}^*_{xL}}{\hat{\beta}^*_{xC}}$ for distance equals 2.6 for exclusively licensed patents compared to 2.2 for the overall sample). This suggests that for exclusively licensed inventions, the greater influence of proximity on licensing, by comparison with its influence on citations, is particularly pronounced. Wald statistics are significant for all of our regressions using data for exclusively licensed patents. Likewise, test statistics for the difference between the panel and pooled estimators are also significant.

The evidence provided in Tables 5 and 6 of greater localization for licensing agreements compared to citation–based spillovers receives further support from the last set of regression specifications in Table 7, which cover non–exclusive licensing agreements and patent citations for the patents associated with these agreements.

*** Table 7 Here ***

Coefficients for $DIST_{i,k}$ and $DISTSQ_{i,k}$, remain statistically significant (and continue to exhibit the upwardly concave U–shape) for nonexclusively licensed patents. Moreover, the negative coefficients for $DIST_{i,k}$ are larger in the licensing specifications 7L2–7L4 relative to the corresponding coefficients in the citation specifications 7C2–7C4, consistent with the findings for the overall sample and the subsample of exclusively licensed patents reported earlier. Comparing the ratio of standardized coefficients for licensing and citation (column 5 of 8), however, reveals that the difference in market/non–market geographic localization is smaller for non–exclusively licensed patents than it is for exclusively licensed patents by almost a factor of two. ($\frac{\hat{\beta}^*_{xL}}{\hat{\beta}^*_{xC}}$ equals 1.4 for non–exclusively licensed patents and 2.6 for exclusively licensed patents). This result is consistent with our earlier finding that the greater influence of proximity on licensing, relative to citations, is particularly large for exclusively licensed inventions. More importantly, the Z-statistic for the difference between the standardized coefficients for licensing and citation for the nonexclusively licensed patents in our sample is only -0.90 and is not significant. This suggests that for nonexclusively licensed inventions, market geographic localization is no more significant for non–market localization.

Wald statistics for the regressions in Table 7 are significant. The statistics for the test $alpha = 0$ are also significant for all but model 7L4. We conducted pooled estimates and found little difference between pooled and panel estimates for model 7L4 of Table 7.

5 Conclusion

Previous studies have found that knowledge–intensive economic interactions tend to benefit from geographic proximity, but have said little about the effects of distance on the flow of knowledge through different channels. This paper compares the geographic "reach" of knowledge flows from university inventions through two important channels:

non-market spillovers exemplified by patent citations and market contracts centered on licensing. We find a consistent tendency for knowledge flows through market transactions (in the narrow sense defined above) to be more geographically localized than those operating through non-market spillovers, contradicting some previous research. This result seems to reflect the necessarily incomplete nature of licensing contracts, as well as the need for licensees to maintain access to know–how that is difficult to transmit through documents, faxes, or even phone or e-mail communication.

The differential effects of distance on licensing and citations are most pronounced (and only statistically significant) for exclusively licensed university patents. This finding may reflect differences between the characteristics of university inventions that are licensed exclusively and non–exclusively. Our interviews with university technology transfer managers suggest that firms seek exclusive licenses for inventions with uncertain commercial potential that require considerable investments in development. Such inventions more closely conform to the "proofs and prototypes" that require the transfer of complementary know–how, as analyzed by Jensen and Thursby (2001) and Arora (1995). But the transfer of such know–how may be less critical for inventions such as research tools that are licensed non–exclusively. These types of inventions tend to require less transfer of tacit know–how from the original inventor and are therefore less constrained by geographic distance.

Universities are an important source of technology and knowledge for firms in many industries. Our study highlights the importance of additional research on how firms manage the acquisition of these technologies through contractual agreements and through spillovers. Knowledge flows embodied in patent licenses and citations co–exist within a broader environment of technology outflows from universities through other channels that include the dissemination of research findings through publication and conferences, sponsorship of research, employment of university graduates, and faculty consulting. Moreover, knowledge flows between universities and industry, particularly in the life sciences, are increasingly governed by materials transfer agreements (MTAs). The channels we examine in this study undoubtedly are affected by and simultaneously affect this broader environment. The interaction of these various channels of market and non-market technology transfer suggests fruitful areas of future research, and we look forward to further investigation in this area.

Table 1: Licenses and Citations to Sample University Patents, 1975-1988

	Columbia University	Stanford University	University of California	University of Michigan	Total Sample
Sample University Patents					
Issued Patents	41	310	498	66	915
Cited Patents	41	309	489	58	897
Licensed Patents	21	208	182	19	430
Patents Licensed Exclusively	13	155	114	15	297
Patents Licensed Non–Exclusively	8	29	24	6	67
Licenses to Sample University Patents					
Total Licenses within 8 Years	63	335	204	48	650
Less Non–Sample Region Licenses	2	27	16	11	56
Less Licenses to Non–Cited Patents	0	1	8	1	10
Total Licenses Remaining in Sample	61	307	180	36	1527
Citations to Sample University Patents					
Total Citations within 8 Years	486	3804	4142	340	8772
Less University Citations	112	683	700	32	1527
Less Non–US Citations	86	1030	1002	78	2196
Less US Government Citations	6	144	89	8	247
Less Other Institution Citations	16	69	134	7	226
Less Citations by Licensees	18	224	75	3	320
Less Non–Sample Region Citations	43	266	355	137	801
Less Citations to Non–Licensed Patents	51	487	1217	27	1782
Total Citations Remaining in Sample	154	901	570	48	1673

Table 2: 51 Sample Regions Shares of Value–Added, Patent Citations, and Licenses

MSA/CMSA	1987 Manuf. Value –Added ($)	% of US 1987 Manuf. Value –Added	US Patent Citations in 8 Years	% of All US Patent Citations	US Licenses in 8 Years	% of All US Licenses
New York CMSA	81,959.2	7.0%	588	9.4%	73	12.1%
Los Angeles CMSA	72,520.5	6.2%	535	8.5%	117	19.4%
Chicago CMSA	49,773.3	4.3%	151	2.4%	12	2.0%
San Francisco CMSA	38,913.2	3.3%	1255	20.0%	169	28.1%
Detroit CMSA	31,043.7	2.7%	81	1.3%	1	0.2%
Boston CMSA	29,713.5	2.5%	602	9.6%	27	4.5%
Philadelphia CMSA	28,940.8	2.5%	156	2.5%	24	4.0%
Dallas CMSA	19,641.4	1.7%	67	1.1%	2	0.3%
Houston CMSA	18,596.9	1.6%	114	1.8%	1	0.2%
Cleveland CMSA	17,262.2	1.5%	101	1.6%	1	0.2%
Minneapolis MSA	15,732.2	1.3%	118	1.9%	9	1.5%
St. Louis MSA	14,115.0	1.2%	48	0.8%	11	1.8%
Atlanta MSA	13,345.7	1.1%	26	0.4%	0	0.0%
Cincinnati CMSA	12,831.7	1.1%	22	0.4%	0	0.0%
Rochester, NY MSA	12,409.0	1.1%	67	1.1%	2	0.3%
Milwaukee CMSA	11,609.4	1.0%	67	1.1%	17	2.8%
Greensboro MSA	10,910.7	0.9%	11	0.2%	0	0.0%
Seattle CMSA	10,895.9	0.9%	112	1.8%	5	0.8%
Baltimore MSA	9,675.6	0.8%	68	1.1%	3	0.5%
Kansas City MSA	9,124.0	0.8%	11	0.2%	4	0.7%
Louisville MSA	8,320.8	0.7%	4	0.1%	0	0.0%
Phoenix MSA	8,179.8	0.7%	44	0.7%	1	0.2%
Charlotte MSA	8,153.6	0.7%	3	0.0%	0	0.0%
Denver CMSA	8,037.3	0.7%	51	0.8%	5	0.8%
Hartford MSA	7,596.9	0.7%	29	0.5%	0	0.0%
Columbus, OH MSA	7,079.1	0.6%	15	0.2%	0	0.0%
Buffalo MSA	7,025.5	0.6%	15	0.2%	0	0.0%
Richmond MSA	6,833.0	0.6%	8	0.1%	0	0.0%
Indianapolis MSA	6,806.0	0.6%	32	0.5%	7	1.2%
Washington DC CMSA	6,788.0	0.6%	217	305%	9	1.5%
Portland, OR CMSA	6,445.4	0.6%	43	0.7%	0	0.0%
San Diego MSA	6,426.8	0.6%	212	3.4%	42	7.0%
Pittsburgh MSA	6,322.8	0.5%	23	0.4%	4	0.7%
Dayton MSA	6,284.6	0.5%	13	0.2%	0	0.0%
Grand Rapids MSA	5,967.7	0.5%	2	0.0%	0	0.0%
Miami CMSA	5,700.2	0.5%	43	0.7%	4	0.7%
Providence MSA	5,493.1	0.5%	8	0.1%	0	0.0%
Nashville MSA	4,989.5	0.4%	3	0.0%	0	0.0%
Greenville MSA	4,967.5	0.4%	2	0.0%	0	0.0%
Toledo MSA	4,925.1	0.4%	14	0.2%	0	0.0%
Raleigh–Durham MSA	4,728.5	0.4%	36	0.6%	5	0.8%
Allentown MSA	4,925.1	0.4%	14	0.2%	0	0.0%
New Orleans MSA	4,314.7	0.4%	37	0.6%	0	0.0%
Norfolk MSA	4,285.3	0.4%	9	0.1%	0	0.0%
Tampa MSA	4,139.8	0.4%	8	0.1%	0	0.0%
Wichita MSA	4,122.8	0.4%	1	0.0%	0	0.0%
Memphis MSA	4,114.2	0.4%	7	0.1%	1	0.2%
Lancaster, PA MSA	3,883.7	0.3%	0	0.0%	0	0.0%
Oklahoma City MSA	3,653.4	0.3%	4	0.1%	0	0.0%
Springfield, MA MSA	3,542.1	0.3%	2	0.0%	0	0.0%
Sacramento, CA MSA	3,542.1	0.3%	2	0.0%	0	0.0%
Total	682,834.9	58.6%	5088	81.1%	557	92.5%
US Total	1,165,746.8	100.0%	6272	100.0%	602	100.0%

Note: Sample regions include largest metropolitan regions by manufacturing value–added in 1987 Economic Census plus the Sacramento MSA.

Table 3: Variable Definitions

Variable	Definition
Dependent Variables	
$\text{LICENSE}_{i,j,k}$	"Number" of licenses to inventing campus i's patents in SIC j from CMSA/MSA k
$\text{CITE}_{i,j,k}$	"Number" of citations to inventing campus i's patents in SIC j from CMSA/MSA k
$\text{EXLIC}_{i,j,k}$	"Number" of licenses to inventing campus i's exclusively licensed patents in SIC j from CMSA/MSA k
$\text{NONEXLIC}_{i,j,k}$	"Number" of licenses to inventing campus i's non–exclusively licensed patents in SIC j from CMSA/MSA k
$\text{EXCITE}_{i,j,k}$	"Number" of citations to inventing campus i's exclusively licensed patents in SIC j from CMSA/MSA k
$\text{NONEXCITE}_{i,j,k}$	"Number" of citations to inventing campus i's non–exclusively licensed patents in SIC j from CMSA/MSA k
Independent Variables	
$\text{DISTANCE}_{i,k}$	Distance (in thousand mile units) between inventing campus i and licensing or citing CMSA/MSA k
$\text{DISTANCESQ}_{i,k}$	Square of distance between inventing campus i and licensing or citing CMSA/MSA k
POP_k, LNPOP_k	Total population in 1990 of CMSA/MSA k; natural log of POP_k
PATIMP_j	Reported importance of formal patent protection in 3–digit SIC_j
SIC283	Indicator variable equal to 1 if SIC j = 283, 0 otherwise
SIC366	Indicator variable equal to 1 if SIC j = 366, 0 otherwise
SIC367	Indicator variable equal to 1 if SIC j = 367, 0 otherwise
SIC382	Indicator variable equal to 1 if SIC j = 382, 0 otherwise
SIC384	Indicator variable equal to 1 if SIC j = 384, 0 otherwise
COLUMBIA	Indicator variable equal to 1 if campus i is Columbia University, 0 otherwise
MICHIGAN	Indicator variable equal to 1 if campus i is in the University of Michigan, 0 otherwise
STANFORD	Indicator variable equal to 1 if campus i is Stanford University, 0 otherwise

Table 4: Descriptive Statistics (Pooled Observations)

Variable	Minimum	Maximum	Mean	Standard Deviation
Independent Variables				
DISTANCE$_{i,k}$	0	2.70	1.60	0.79
POP$_k$	422,822	19,800,000	2,701,540	3,431,347
VALADD$_{a\|j,k}$	0	8,548.90	900.73	1,321.23
PATIMP$_j$	1.50	6.53	4.15	1.11
Dependent Variables				
Overall University Patent Sample, N = 12,240				
LICENSE$_{i,j,k}$	0	18.83	0.04	0.44
CITE$_{i,j,k}$	0	28.54	0.12	0.85
Exclusively Licensed Patent Sample, N = 11,016				
LICENSE$_{i,j,k}$	0	12.64	0.03	0.31
CITE$_{i,j,k}$	0	21.45	0.11	0.75
Non–Exclusively Licensed Patent Sample, N = 11,016				
LICENSE$_{i,j,k}$	0	10.32	0.02	0.21
CITE$_{i,j,k}$	0	12.42	0.03	0.30

Table 5: Poisson Regression, Overall University Patent Sample

	Dependent Variables = LICENSE, CITE							
	Quasi–Maximum Likelihood Panel Poisson Estimates							
	LICENSES				CITATIONS			
Model No.	5L1	5L2	5L3	5L4	5C1	5C2	5C3	5C4
Model Type	Basic Controls	Add Distance	Add Univ.	Add Tech.	Basic Controls	Add Distance	Add Univ.	Add Tech.
LNPOP	1.07*** (0.07)	1.07*** (0.07)	1.02*** (0.07)	1.02*** (0.07)	1.16*** (0.05)	1.18*** (0.05)	1.13*** (0.05)	1.10*** (0.05)
PATIMP	0.49*** (0.05)	0.49*** (0.05)	0.55*** (0.05)	0.13* (0.08)	0.21*** (0.03)	0.21*** (0.03)	0.31*** (0.03)	-0.11** (0.05)
NOTINYALE	0.98** (0.48)	0.97** (0.48)	1.33*** (0.48)	0.24 (0.51)	0.33 (0.27)	0.37 (0.26)	0.83*** (0.27)	-0.18 (0.28)
CALIFORNIA	2.24*** (0.15)	1.24*** (0.19)	1.16*** (0.20)	1.17*** (0.20)	1.10*** (0.10)	0.61*** (0.14)	0.66*** (0.16)	0.63*** (0.15)
NORTHEAST	0.63*** (0.17)	0.12 (0.21)	0.39* (0.21)	0.42** (0.21)	0.50*** (0.10)	-0.19 (0.13)	0.15 (0.15)	0.16 (0.14)
DISTANCE[A]		-2.56*** (0.36)	-2.19*** (0.38)	-2.19*** (0.36)		-1.73*** (0.25)	-1.12*** (0.28)	-1.22*** (0.28)
DISTANCESQ[B]		0.82*** (0.14)	0.64*** (0.14)	0.64*** (0.14)		0.68*** (0.09)	0.38*** (0.10)	0.42*** (0.10)
COLUMBIA			0.70*** (0.19)	0.73*** (0.18)			0.48*** (0.12)	0.50*** (0.12)
MICHIGAN			0.04 (0.25)	0.06 (0.25)			-19.32 (1858.02)	-20.21 (2949.86)
STANFORD			2.55*** (0.12)	2.55*** (0.12)			2.41*** (0.08)	2.43*** (0.08)
SIC283				2.35*** (0.23)				2.58*** (0.17)
SIC366				0.98*** (0.24)				1.37*** (0.14)
SIC367				0.68 (0.25)				1.29*** (0.14)
SIC382				2.29*** (0.16)				2.20*** (0.12)
SIC384				2.21*** (0.17)				2.36*** (0.12)
YEAR EFFECTS	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.
CONSTANT	-22.70 (1.07)	-21.13 (1.08)	-21.51 (1.08)	-20.39 (1.05)	-22.10 (0.74)	-21.61 (0.74)	-22.03 (0.75)	-20.63 (0.73)
No. of Obs.	97,920	97,920	97,920	97,920	97,920	97,920	97,920	97,920
No. of Groups	12,240	12,240	12,240	12,240	12,240	12,240	12,240	12,240
Log Pseudo Likelihood	-2005	-1966	-1756	-1595	-5259	-5229	-4695	-4351
Wald	1608.6***	1664.4***	1936.9***	2311.3***	1432.4***	1528.1***	1999.2***	2536.6***
$\chi^2(\alpha=0)$	453.5***	419.05***	175.22***	32.17***	1904.96***	1759.04***	958.53***	401.4***

[A]Units in 1,000 miles
[B]Units in (1,000 miles)^2
Standard errors in parentheses
*** p>0.01 ** p>0.05 * p> 0.10

Table 6: Poisson Regression, Exclusively Licensed University Patent Sample

	Dependent Variables = LICENSE, CITE							
	Quasi–Maximum Likelihood Panel Poisson Estimates							
	LICENSES				CITATIONS			
Model No.	6L1	6L2	6L3	6L4	6C1	6C2	6C3	6C4
Model Type	Basic Controls	Add Distance	Add Univ.	Add Tech.	Basic Controls	Add Distance	Add Univ.	Add Tech.
LNPOP	1.11*** (0.09)	1.14*** (0.09)	1.10*** (0.09)	1.11*** (0.09)	1.12*** (0.05)	1.13*** (0.05)	1.07*** (0.05)	1.05*** (0.05)
PATIMP	0.38*** (0.06)	0.38*** (0.06)	0.43*** (0.06)	0.18*** (0.09)	0.21*** (0.04)	0.18*** (0.03)	0.25*** (0.04)	-0.13*** (0.05)
NOTINYALE	0.91* (0.52)	0.90* (0.52)	1.18** (0.52)	0.21 (0.57)	0.30 (0.28)	0.33 (0.28)	0.68** (0.28)	-0.17 (0.30)
CALIFORNIA	2.42*** (0.19)	1.46*** (0.23)	1.06*** (0.28)	1.08*** (0.27)	0.97*** (0.11)	0.53*** (0.15)	0.23 (0.19)	0.18 (0.18)
NORTHEAST	0.61*** (0.23)	0.09 (0.28)	0.36 (0.29)	0.38 (0.28)	0.52*** (0.10)	-0.09 (0.14)	0.31** (0.16)	0.31** (0.15)
DISTANCE^A		-2.54*** (0.43)	-2.61*** (0.46)	-2.55*** (0.45)		-1.56*** (0.26)	-1.31*** (0.31)	-1.44*** (0.31)
DISTANCESQ^B		0.82*** (0.17)	0.77*** (0.17)	0.74*** (0.14)		0.61*** (0.10)	0.37*** (0.11)	0.42*** (0.11)
COLUMBIA			-0.51 (0.33)	-0.49 (0.32)			-0.21 (0.16)	-0.20 (0.16)
MICHIGAN			-0.15 (0.32)	-0.15 (0.32)			-19.88 (2263.11)	-19.90 (2304.98)
STANFORD			2.15*** (0.12)	2.17*** (0.14)			2.26*** (0.08)	2.29*** (0.08)
SIC283				2.25*** (0.30)				2.44*** (0.19)
SIC366				1.08*** (0.27)				1.39*** (0.14)
SIC367				0.87*** (0.29)				1.43*** (0.15)
SIC382				2.18*** (0.20)				2.24*** (0.12)
SIC384				2.25*** (0.21)				2.38*** (0.13)
YEAR EFFECTS	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.
CONSTANT	-23.32 (1.07)	-22.13 (1.08)	-22.12 (1.35)	-21.28 (1.34)	-21.34 (0.78)	-20.92 (0.79)	-20.58 (0.80)	-20.63 (0.73)
No. of Obs.	88,128	88,128	88,128	88,128	88,128	88,128	88,128	88,128
No. of Groups	11,016	11,016	11,016	11,016	11,016	11,016	11,016	11,016
Log Pseudo Likelihood	-1276	-1250	-1133	-1033	-4491	-4470	-4002	-3700
Wald	1104.4***	1135.6***	1323.1***	1515.3***	1188.1***	1255.0***	1704.2***	2179.5***
$\chi^2(\alpha=0)$	188.88***	177.31***	76.32***	15.00***	1403.42***	1303.71***	665.87***	252.03***

^{A}Units in 1,000 miles
^{B}Units in (1,000 miles)^2
Standard errors in parentheses
*** p>0.01 ** p>0.05 * p> 0.10

Table 7: Poisson Regression, Non–Exclusively Licensed University Patent Sample

	Dependent Variables = LICENSE, CITE							
	Quasi–Maximum Likelihood Panel Poisson Estimates							
	LICENSES				CITATIONS			
Model No.	7L1	7L2	7L3	7L4	7C1	7C2	7C3	7C4
Model Type	Basic Controls	Add Distance	Add Univ.	Add Tech.	Basic Controls	Add Distance	Add Univ.	Add Tech.
LNPOP	0.89*** (0.09)	0.88*** (0.09)	0.91*** (0.10)	0.88*** (0.09)	1.01*** (0.08)	1.03*** (0.08)	1.07*** (0.08)	1.04*** (0.08)
PATIMP	0.65*** (0.07)	0.64*** (0.07)	0.67*** (0.07)	0.23* (0.12)	0.40*** (0.05)	0.39*** (0.05)	0.45*** (0.05)	-0.12 (0.09)
NOTINYALE	0.25 (1.34)	0.22 (1.34)	0.35 (1.34)	-0.74 (1.40)	0.43 (0.57)	0.41 (0.56)	0.70 (0.58)	-0.89 (0.61)
CALIFORNIA	1.97*** (0.21)	1.02*** (0.26)	1.09*** (0.29)	0.98*** (0.28)	1.84*** (0.17)	1.18*** (0.21)	1.33*** (0.24)	1.31*** (0.23)
NORTHEAST	0.89*** (0.23)	0.37 (0.28)	0.48 (0.31)	0.41 (0.30)	0.80*** (0.18)	-0.10 (0.22)	0.20 (0.25)	0.18 (0.25)
DISTANCE^{A}		-2.66*** (0.50)	-1.96*** (0.57)	-2.35*** (0.58)		-2.65*** (0.40)	-1.56*** (0.48)	-1.70*** (0.47)
DISTANCESQ^{B}		0.86*** (0.19)	0.57*** (0.212)	0.72*** (0.22)		1.03*** (0.09)	0.59*** (0.18)	0.64*** (0.17)
COLUMBIA			1.62*** (0.25)	1.64*** (0.24)			1.31*** (0.17)	1.31*** (0.17)
MICHIGAN			0.04 (0.44)	0.06 (0.43)			-18.19 (2434.68)	-19.84 (5596.10)
STANFORD			2.90*** (0.20)	2.86*** (0.19)			2.40*** (0.14)	2.37*** (0.14)
SIC283				2.41*** (0.33)				3.09*** (0.28)
SIC366				0.97*** (0.39)				1.70*** (0.21)
SIC367				0.45 (0.46)				0.88*** (0.29)
SIC382				2.50*** (0.22)				1.98*** (0.20)
SIC384				2.17*** (0.23)				2.28*** (0.21)
YEAR EFFECTS	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.
CONSTANT	-21.58 (1.41)	-19.81 (1.43)	-21.68 (1.49)	-20.00 (1.46)	-22.62 (0.74)	-21.77 (1.17)	-23.72 (1.24)	-21.76 (1.22)
No. of Obs.	88,128	88,128	88,128	88,128	88,128	88,128	88,128	88,128
No. of Groups	11,016	11,016	11,016	11,016	11,016	11,016	11,016	11,016
Log Pseudo Likelihood	-1024	-1001	-869	-777	-1727	-1703	-1525	-1393
Wald	648.6***	691.0***	851.7***	1187.3***	665.6***	712.7***	832.1***	1063.0***
$\chi^2(\alpha$=0)	72.83***	61.34***	23.05***	0.24	169.15***	147.72***	93.54***	27.69***

^{A}Units in 1,000 miles
^{B}Units in (1,000 miles)^2
Standard errors in parentheses
*** p>0.01 ** p>0.05 * p> 0.10

Table 8: Standardized Coefficients and Hypothesis Tests: $H_0 : \hat{\beta}^*_{xL} - \hat{\beta}^*_{xC} = 0$

	Standardized Coefficient LICENSES ($\hat{\beta}^*_{xL}$)	Standardized Coefficient CITATIONS ($\hat{\beta}^*_{xC}$)	$\hat{\beta}^*_{xL} - \hat{\beta}^*_{xC}$	Z-statistic	$\frac{\hat{\beta}^*_{xL}}{\hat{\beta}^*_{xC}}$
	(1)	(2)	(3)	(4)	(5)
Overall University Sample					
$LNPOP$	7.60	6.66	0.94	1.66	1.1
$PATIMP$	1.53	-1.07	2.60	2.55***	-1.4
$DISTANCE$	-15.01	-6.82	-8.19	-2.81***	2.2
Exclusively Licensed Patents					
$LNPOP$	10.84	6.97	3.87	1.56	1.6
$PATIMP$	0.57	-1.40	1.97	1.29	-0.4
$DISTANCE$	-23.29	-8.92	-14.37	-3.19***	2.6
Nonexclusively Licensed Patents					
$LNPOP$	13.76	16.18	-2.42	-1.31	0.9
$PATIMP$	5.68	-3.02	8.70	2.33***	-1.9
$DISTANCE$	-34.35	-24.58	9.77	-0.90	1.4

Note: Standard errors in parentheses
*** p>0.01 ** p>0.05 * p> 0.10

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