The Influence of University Research on Industrial Innovation*

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Abstract

We use U.S. patent records to examine the role of research personnel as a pathway for the diffusion of ideas from university to industry. By examining an inventor's patenting history contained in the patent data, we can determine whether an inventor on a firm's patent had previously appeared as an inventor on a patent assigned to a university. Appearing on a patent assigned to a university is evidence that the inventor had exposure to university research, either directly as a university researcher or through some form of collaboration with university researchers. We also use data from the Dissertation Abstracts to establish whether the inventor has an advanced degree (doctorate or master's), another measure of exposure to university research. We find a steady increase in university influence in both measures over the period 1979-97. Moreover, in our analysis of the pharmaceutical and semiconductor industries over the decade of the 1990s we find (1) the pharmaceutical industry makes greater use of inventors with university backgrounds than the semiconductor industry, (2) the percentage of patents assigned to firms that involved inventors with a university background increased substantially in both industries, and (3) that large and highly capitalized firms in both industries and young firms in the pharmaceutical industry are disproportionately active in the diffusion of ideas from the university sector.

JEL Classification: J62, O31, O33
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I. Introduction

This paper examines the influence of university research on innovation in industry. The results of university research disseminate along a number of pathways: through scholarly publications and the material published in universities' patent applications, at conferences where industry and academic research personnel commingle and where scholarly work is presented, and via informal social networks.[1] But firms also learn about university research after employing or collaborating with researchers who work or have worked in university laboratories. In fact, social scientists who study innovation suspect that certain kinds of important knowledge become available to a firm only with sustained, close interaction with researchers who possess this knowledge as through an employment or collaborative research arrangement.

We use U.S. patent data to study the role of research personnel as a pathway for the diffusion of ideas from university to industry. The inventors behind the patented invention are listed on each patent, as are the firms, government organizations, and universities to which the patents are assigned. Using a procedure similar to one proposed by Trajtenberg (2004), we match names on patents to construct a panel data set of inventors that contain the patents in each year of the inventors' careers. We are thus able to identify for each inventor when and how often he or she is innovating for university and industry assignees. For each patent assigned to industry, therefore, we can tell whether its inventors had previously appeared as an inventor on a patent assigned to a university. Appearing on a patent assigned to a university is evidence that the inventor had exposure to university research, either directly as a university researcher or through

[1] See Cohen, Nelson and Walsh (2002) on the various means by which innovating firms accesses know-how developed externally. See Agrawal, Cockburn, and McHale (2003) for evidence of the importance of social networks in promoting diffusion.

some form of collaboration with university researchers. We also use data from the Dissertation Abstracts to establish whether the inventor has an advanced degree (doctorate or master's), another measure of exposure to university research. In this paper, we investigate how the influence of university research on industry innovation has evolved over the last two decades, through inventors' university inventing and research experience.

We also use patent citations to infer the extent of industry access to university-produced knowledge and how that access has changed. Patent applicants are legally obligated to disclose any knowledge they have of previous relevant inventions. The patent examiner may add to the application relevant citations omitted by the applicant. Thus, through the patent citations each patent documents the "prior art" upon which the new innovation builds, and because we know each cited patent's assignee type, we know whether the prior art originated in university laboratories.[2]

Another objective of our paper is to identify factors that influence an innovating firm's interaction with university R&D, especially in the pharmaceutical and semiconductor industries. We focus on these two industries since they are prolific generators of innovations and patents. After combining the inventor panel data with firm information in these industries, we relate various firm-level characteristics with our measures of exposure to university research to sort out the factors that influence an innovating firm's interaction with university research. We also repeat the analyses conducted on the comprehensive industry-wide data separately for the pharmaceutical

[2] Other studies have examined citations to university patents, but to our knowledge, none have looked at how the phenomenon is evolving (e.g., Jaffe and Trajtenberg, 2002).

and semiconductor industries to find how the influence of university research has evolved in these two industries.

Our main findings are the following. Over the period 1979-1997, we find industry increased its employment of inventors with experience on university research projects and with advanced university degrees. For the decade of the 1990s we also find (1) the pharmaceutical industry made greater use of inventors with university backgrounds than the semiconductor industry, (2) the percentage of patents assigned to firms that involved inventors with university backgrounds increased substantially in both industries, and (3) that large and highly capitalized firms in both industries and young firms in the pharmaceutical industry were disproportionately active in the diffusion of ideas from the university sector.

The paper is organized as follows. The next section summarizes the literature on the various mechanisms for university technology transfer to industry, technology spillovers, scientist collaboration and mobility, and the use of patent citations to trace technological diffusion. Section III describes our data, focusing on the construction of the inventor panel. Section IV describes levels and trends in university involvement in all industries and by industry. Section IV also describes our empirical estimation of the determinants of firm use of university-experienced inventors and inventors with advanced degrees, and of citations to university patents. Section V offers concluding remarks.

II. Literature Review

A raft of empirical work suggests important and pervasive effects of university research on industry R&D and innovation (e.g., Jaffe, 1989; Adams, 1990; Mansfield, 1991, 1998; Nelson and Rosenberg, 1993; Cohen, Nelson, and Walsh, 2002).[3] Mansfield (1991) roughly estimates the annual social rate of return to university research over the years 1975 through 1978 to be 28 percent. While the diffusion of technology from the academic to the industrial sector is thought to be important, little is known about the transmittal mechanisms. Scholars writing in both the economics and sociology of innovation literatures argue that new technologies are frequently difficult to transmit to the uninitiated via spoken or written communication (see Polyani, 1958, for an early discussion of the 'tacit' knowledge). Often the most efficient means of transmission across organizational boundaries for tacit knowledge is via person-to-person contact involving a transfer or exchange of personnel. Recent findings that technological diffusion appears to be geographically limited (e.g., Jaffe, 1989; Jaffe, Trajtenberg, and Henderson, 1993; Zucker, Darby, and Brewer, 1998; and Mowery and Ziedonis, 2001) is often interpreted as evidence of the tacitness of knowledge.

More direct evidence exists that person-to-person interaction is important for the diffusion of technology. Cohen, Nelson, and Walsh (2002) surveyed R&D managers on the means by which they gather and assimilate new technologies. They find that firms access externally-located technology partly through the hiring of and collaboration with researchers from the outside. Moreover, they find that hiring/collaboration with outside scientists is complementary to other means of accessing externally produced knowledge, such as through informal communications with outsiders and more formal (such as consulting) relationships with outsiders. Almeida and Kogut (1999) find that scientific references that firms cite in their patent applications reflect the employment histories of their inventors, suggesting that ideas in the semiconductor industry are spread by the

[3] See Cohen, Florida, Randazzese, and Walsh (1998) for a survey of this evidence.

movement of key engineers among firms, especially within a geographical area.[4] Zucker, Darby, and Armstrong (2001) find evidence of a pay-off to firms that seek interactions with outside researchers. They find a positive impact on patent productivity for biotech firms that collaborate with university researchers on research and scholarly publications.

We therefore anticipate that the evidence, while presently incomplete, will eventually show that the migration of university-experienced scientific personnel to industry is an important means of technology transfer and that it complements other mechanisms. Assuming this to be the case, we use measures of the industrial employment of university-experienced researchers to track the extent to which industry is accessing university technologies.

We also use patent citations to track the diffusion of university innovations. Some scholars have used citations to university and industrial patents to compare the relative importance of innovations arising from these sectors and to examine how changes in patent law have influenced the importance of university patents (Henderson, Jaffe, and Trajtenberg, 1998; Sampat, Mowery, and Ziedonis, 2003). Others have looked at the determinants of a university patent's likelihood of being cited (Jaffe and Trajtenberg, 2002). To our knowledge, ours is the first study that examines the extent to which industrial patents cite university patents.

III. Data Description

Our data are derived from six sources: (1) Patent Bibliographic data (Patents BIB) released by the U.S. Patent and Trademark Office (USPTO) that contain bibliographic

[4] See also the (indirect) evidence of a link between scientific mobility and technological diffusion in Kim and Marschke (2005) and Moen (2005).

information for U.S. utility patents issued from 1969 to 2002; (2) the ProQuest Digital Dissertation Abstracts database which contains information on the date, field, and type of degree for those who earned degrees in all natural science and engineering fields between 1945-2003; (3) the Compact D/SEC database since 1989 which contains firm information taken primarily from 10-K reports filed with the Securities and Exchange Commission; (4) the Standard & Poor's Annual Guide to Stocks-Directory of Obsolete Securities which include a history of firm name changes; (5) the Thomas Register, Mergent, and Corptech data which report a firm's founding year, and finally (6) the NBER Patent-Citations data collected by Hall, Jaffe and Trajtenberg (2001) which contain all citations made by patents granted in 1975-1999. To create our database from these sources, we first match inventor names in the Patents BIB and Dissertation Abstracts databases. We then match firms in the Compact D/SEC database to assignees in the Patent BIB database with founding information added. Finally, we combine the two databases from the first two steps and add information from the citation data.

Inventor name matching

The methodology for inventor name matching is similar to that in Trajtenberg (2004). To start, we treat each entry that appears in the inventor name field of every patent in the Patents BIB data as a unique inventor. Given, let's say, N number of names in this name pool we match each name to all other names, which generates N(N-1)/2 number of unique pairs. For each pair, we consider the two names as belonging to the same inventor if the SOUNDEX codes of their last names and their full first names are the same, and at least one of the following three conditions is met: (1) the full addresses for the pair of names are the same; (2) one name from the pair is an inventor of a patent that is cited by another patent whose inventors include the other name from the pair; or (3) the two names from the pair share the same co-inventor (see Appendix A for the SOUNDEX coding method). These three criteria in our name matching method are the same as the "Strong" criteria of Trajtenberg (2004). We use the SOUNDEX coding method to expand the list of similar last names to overcome the potential for misspellings and inconsistent foreign name translations to English; misspellings are common in the USPTO data as are names of non-Western European origin. As an additional step beyond the SOUNDEX method, we impose the criterion for matching that a pair of names is not treated as a match if their middle name initials are different.

We also consider a pair of names as a match if two have the same full last and first names, and at least one of the following two conditions is met: (1) the two have the same zip code; or (2) they have the same full middle name. These two criteria correspond to the "Medium" criteria of Trajtenberg (2004).

Given all pairs of names that are considered as matches by the preceding procedures, we then impose transitivity in the following sense: If name A is matched to name B and name B is matched to name C, name A is then matched to name C. We iterate this process until all possible transitivity matches are completed. At this point we assign the same inventor ID number for all the names matched.

Trajtenberg (2004) assigns scores for each matching criteria and considers a pair matched only if its total score from all matching criteria exceeds a threshold. We do not use this score method in our data construction because different scores given to each criterion and the threshold score can be quite arbitrary. Our methods also differ in that we do not employ some other criteria used in Trajtenberg such as matching the pair of names with the same assignee because those criteria can yield name matching with a bias in mobility among inventors. Instead we apply the criterion that a pair of names is not treated as a match if their middle name initials differ. In the end, because of these differences the number of distinctive inventors identified with our procedure is a little higher than that with the method in Trajtenberg. We identified 2.3 million unique inventors (45%) out of 5.1 million names in the entire patent data while Trajtenberg (2004) found 1.6 million distinctive inventors (37%) out of 4.3 million names. Note that our patent database is larger because it includes additional years, 1969-1974, and 2000-2002.

After name matching in the patent data, we match the Dissertation Abstract data to the inventors in the patent data. Each inventor identified through the preceding procedure may have a list of names matched to him or her (for example, John Maynard Keynes, John M. Keynes, John Keynes) due to names linked to each other by satisfying the criteria described above. Since the Dissertation Abstract data contain for each individual a full name in a string instead of separate last, first and middle name fields, we convert all the names under each inventor ID number in the patent data to strings to search for them within the Dissertation Abstract data.[5] On rare occasions when multiple names from the Dissertation Abstract data are matched to one ID number in the patent data, we randomly pick one name. Out of 2.3 million unique inventors in our patent data, 3 percent (64,507) are identified as holders of advanced degrees.

[5] In addition, we impose conditions regarding the timeframe of the inventor's patenting history, wherein the inventor's last patent is no later than forty years following the dissertation date, and the first patent is no more than twenty years before the dissertation date.

Firm-assignee matching

We choose all firms whose primary SIC code is 2834 (pharmaceutical preparation) or 3674 (semiconductor and related devices) in the Compact D/SEC data.[6] We select these two industries for our study because the firms in these industries are active in patenting and produce homogenous products relative to other industries. By focusing on two relatively homogenous industries, we avoid problems due to the incomparability in utility and marketability of innovations, and in patent propensities across industries. Note that we select only the years 1989 through 1997 for our study, because the Compact D/SEC data before 1989 are unavailable to us and we found that starting with application year 1998 the patent time series tailed off due to the review lag at the USPTO.

Because parent firms patent sometimes under their own names and at other times under the names of their subsidiaries, merging the Patents BIB data with firm-level data in the Compact D/SEC data is not straightforward. Mergers and acquisitions at both the parent firm and subsidiary levels, common in these two industries during the 1990s, and name changes further complicate linking the patent to firm-level data. (The USPTO does not maintain a unique identifier for each patenting assignee at the parent firm level nor does it track assignee name changes.) Thus, to use the firm-level information available in the Compact D/SEC data, the names of parent firms and their subsidiaries and the ownership of firms must be tracked over the entire period of the study, which is accomplished based on the subsidiary information in the Compact D/SEC data.

[6] Because the Compact D/SEC database contains only publicly traded firms that have at least $5 million in assets, our sample contains firms that are on average larger and more successful than the firms in the general population in these industries.

Since the Compact D/SEC data do not report old names of the firms that change their names (in many cases, after mergers), we use the S&P data to track the history of name changes of each assignee and link firm level information in the Compact D/SEC data before and after a name change. Finally, we merge information on firms' founding years to the firm database.

Combining databases from the preceding steps

As the final step, we link the patent inventor database from the first step to the firm database from the second step to produce a data set on inventors and patents that includes firm-level data (e.g., R&D expenditures, sales, and employment level) on the patents' assignees. Because patents are typically assigned to the firm (the *assignee*) that employs the inventors, we identify the inventors' employers in the Patents BIB data by patent assignees. We then add information on all citations from the NBER Patent-Citations data collected by Hall, Jaffe and Trajtenberg (2001) where each citing patent that was granted between 1975 and 1999 is matched to all patents cited by the patent.

IV. Results

Trends

Figures 1A, B, and C show the annual percentage of industry-assigned patents that list at least one inventor who had previously been named an inventor on a university-assigned patent applied for sometime in the previous ten years (UNIV).[7] Because our data included patents granted in 1969 and later, we imposed a cut-off for the patents used

[7] Our university assignees include domestic universities, hospitals, research laboratories (non-government), and non-profit organizations in the U.S.

to define whether an inventor was university-experienced at the time of the industry patent's application. We chose to consider only those university-assigned patents on which the inventor appeared in the ten years prior to the date of the industry patent's application because ten years still leaves us a long period over which to conduct our analysis and because skills or knowledge acquired in a university setting far in the past may not be very valuable. Figure 1A shows this measure for all patents granted to U.S. industry assignees by application year for the years 1979 through 1997. Figures 1B and C isolate the pharmaceutical and semiconductor industries, respectively, for the period 1989 through 1997.

Figure 1A shows a steady increase in UNIV between 1979 and 1995, from 0.5 to 2.6 percent. UNIV then drops from 2.6 percent in 1995 to 1.9 percent in 1996 before recovering somewhat in 1997. This precipitous rise and fall of UNIV is puzzling—we observe this phenomenon in the other figures discussed below—but may be related to a change in patent law in 1995. Until 1995, successful patent applicants received a 17 year monopoly on the use of their invention from the date the patent was granted. For applications filed after June 8, 1995, patented applicants received a 20 year monopoly commencing from the date of the patent application. This new law may have changed the duration of the monopoly for many patent holders, affording longer monopoly periods for patents that are approved quickly, and shorter periods for patents whose review procedure is delayed, as by an appeal or an interference proceeding. In addition, the new law provided that patents applied for prior to June 8, 1995 and issuing on or after June 8 would expire either 17 years from issuance, or 20 years from the data of original application, whichever generated the longer monopoly period (Radack, 1995; Elman, Wilf, and Fried, 1995). These relatively generous terms may have for the short transitional period made some marginal innovations worth the opportunity cost of patenting. Figure A in the appendix shows the patent applications by application year over the period 1979 through 1997. The applications time series show a distinctive blip in 1995 that may reflect a rush to file applications before the June 7 expiration date to take advantage of the opportunity to lock in an extended monopoly period. Moreover, because basic research has a longer shelf life, firms with inventions constituting basic research may have been especially keen to obtain the longer monopoly period. Thus it seems to us natural to see an increase in university influence in our figures during the transition period.[8]

Figures 1B and C show the measure UNIV for firms in the pharmaceutical and semiconductor industries, respectively, for the period 1989 through 1997. First, note in this period in both industries an increase in the percentage of patents that name at least one inventor who has invented for university-assigned patents. Second, note that patents in the pharmaceutical industry were more likely than those in the semiconductor industry to include an inventor who had university patent experience: over this period, about 6.6 percent of patents in the pharmaceutical industry included at least one inventor with university patenting experience compared to about 1.9 percent in the semiconductor industry. Also note that the rate of increase was greater for the semiconductor industry. Finally, note in 1995 the blip in the pharmaceutical time series, which is absent in the

[8] Another possibility we considered was a truncation effect. Our data set may exclude some patents applied for in the late 1990s that had not been granted by February 2002, the end date of our data. Thus, if the more complicated patent applications tend also to be the patent applications involving university-experienced inventors, than our time series might trail off at the end of the period, as depicted in Figure 1A. We tested this hypothesis by using the patent granting dates to truncate the data artificially; we tossed out all patents that had not been granted as of (the arbitrarily chosen year) 1994. This failed to produce a blip leading us to conclude this phenomenon is not caused by truncation.

semiconductor time series. For the pharmaceutical industry the length of time of the monopoly may be more important as pharmaceutical patents typically still earn substantial revenues at the end of the monopoly period (Elman et al, 1995), suggesting the deadline may have provoked a greater behavioral response in the pharmaceutical industry.

Figures 2A, B and C show the percentage of patents that include at least one inventor with an advanced degree (ADVDEG). Figure 2A shows this figure for all patents granted to U.S. industry assignees. Figures 2B and C show only the pharmaceutical and semiconductor industries, respectively. Figure 2A shows a steady increase in ADVDEG from 1983 until 1995, where it dips slightly in 1996, and then begins to rise again between 1996 and 1997. ADVDEG averages 33 percent for the pharmaceutical industry and 19 percent for the semiconductor industry. This indicates that both industries rely significantly more on highly-educated labor for research as the averages in both industries are higher than the overall average in the full data set during the same period. Figures 2B and C confirm the findings in Figures 1B and C in that (1) both time series increase through the period, (2) the level is higher in the pharmaceutical industry, but the rate of increase is higher for the semiconductor industry, and (3) the time series for the pharmaceutical industry demonstrate a blip centered at 1995.

One possible explanation for rising ADVDEG over time is an increase in the supply of inventors with advanced degrees in the labor market. Figure 2D indicates that the number of graduates with advanced degrees from U.S. higher education institutions as a fraction of the number of graduates with bachelor’s degrees has not increased much. This implies that a rising number of highly educated inventors in innovation may not be attributed to a supply change. Note, however, that Figure 2D excludes the number of foreign educated inventors with advanced degrees.

Figures 3A, B, and C show the annual percentage of industry-assigned patents that cite a university patent applied for within the previous ten years as prior art (UCITE). Figure 3A displays UCITE for all industries for the period 1979 through 1997. Figures 3B and C display UCITE for the pharmaceutical and semiconductor industries, respectively. Figure 3A shows a steady increase in UCITE between 1979 and 1995 from 1.4 percent to 9.7 percent, followed by a decline through the end of the period. Qualitatively, Figures 3B and C display similar patterns to those displayed by Figures 1B and C and 2B and C: UCITE's average level is higher for the pharmaceutical industry and in both industries UCITE rises over time. In both industries, UCITE peaks in 1995, but the drop off is more striking in the pharmaceutical industry. Figures 3B and C show an approximately two-fold increase in the relative importance of university patents in both industries.

UNIV and ADVDEG give us a sense of the extent that R&D projects involve inventors with at least some exposure to university research (either through the pursuit of an advanced research degree or as part of a research team that innovated for a university) and whether this phenomenon is increasing over time. However, these measures allow us to look only at whether research teams involve university-experienced inventors but not at how many university-experienced inventors are involved in the firms' research. Moreover, if the size of the research group is changing, then our results showing an increase in UNIV and ADVDEG may mislead us to conclude that the utilization of university experience is intensifying when really the increasing size of research groups is raising the chances that groups include a university-experienced inventor. We therefore repeated the exercises for Figures 1 and 2 but used as our measure the fraction of unique patenting inventors who had previous university patenting experience. We found that these alternative measures to UNIV and ADVDEG demonstrate qualitatively similar results (these figures are available upon request).

Determinants of university influence

We are interested in learning which firms access university research. For example, are there scale or scope economies in exploiting university research that favor large or diversified firms? Do young firms that are developing and using new technologies make greater use of university research than older firms? Tables 2, 3, and 4 present the results of our estimation of the determinants of accessing university research. These regressions relate measures of the firm's access to university research in year t and firm characteristics. The dependent variables in Tables 2, 3, and 4 are the logit transform of the fractional form of the variables defined in Figures 1, 2, and 3, that is, of UNIV, ADVDEG, and UCITE, respectively. We should note, however, that these variables in our regressions are defined at the firm level, not at the economy or industry level. All models are estimated with random (firm) effects.

The means and standard deviations of the independent and dependent variables, along with their definitions, are described in Table 1.[9] All right-hand side variables are logged. The base specification includes a measure of organizational size, either the

[9] Note that the means of the patent percentages in the figures for the two industries are not equal to those reported in Table 1 because in Table 1 we average the percentages of patents for firms in each industry while the figures show the total number of university-affiliated patents in an industry as a ratio to the total number of patents assigned to the industry.

number of employees (EMPLOYEE) or R&D expenditures (R&D), to examine the effect of economies of scale at the firm level or R&D enterprise level, respectively. The base specification also includes the capital labor ratio (K/L) and the number of business lines in the firm (NSIC), measured by the number of secondary SIC's identified with the firm. We include the capital-labor ratio (K/L) as a regressor because a highly capitalized firm may rely on more advanced technology, which may be reflected in the nature of its innovation, or lead the firm to use skilled labor more intensively. We include NSIC as a regressor to estimate the impact of economies of scope on how a firm's reliance on university-originated research.

The results for the basic specification are included in the first two columns of each panel. They consistently show a positive effect of firm size on the use of inventors with university patenting experience (Table 2) and on the use of inventors with advanced degrees (Table 3), in both industries. Size also increased the likelihood that a firm's patents cited university-assigned patents but only among semiconductor firms. The coefficient estimate on log K/L is generally positive and significant in the UNIV regressions for the semiconductor industry, positive and significant in the ADVDEG regressions for both industries, and in the UCITE regressions inconsistently positive and significant for the semiconductor industry and insignificant for the pharmaceutical industry. A general positive effect of K/L may be due to the fact that firms with higher capital intensity are typically involved with more advanced technology and thus more technically advanced patents, which should rely more on basic research results from universities. Also, capital-intensive firms are shown in the labor literature to employ more skilled or highly-educated workers, which explains the positive relation between

K/L and ADVDEG (see Griliches, 1969, Goldin and Katz, 1998, for evidence on capital-skill complementarity). The coefficient estimate on log NSIC is never significant by conventional criteria of significance.

The third column in each panel describes the results from estimations that include two additional regressors: median experience of all inventors in a firm (MEXP) and years elapsed since the founding year of a firm (FIRMAGE). Adding these two variables substantially increases the R squared of the pharmaceutical industry regressions. The coefficient estimate on log MEXP is positive and significant for both industries for the UNIV regressions. This may partly reflect that inventors who are more experienced are also more likely to have invented for a university assignee. We also observe a positive and significant relationship between median experience and UCITE. The coefficient estimate on log FIRMAGE is negative in most cases and is negative and significant in the pharmaceutical regressions with UNIV and marginally significant and negative with ADVDEG as the dependent variables. That is, we find evidence that older firms in the pharmaceutical industry employ fewer inventors with university patenting experience.

The key variables in our estimation may be time trended, in which case the estimated effect of our independent variables on our measures of university research influence could be spurious. To test the sensitivity of our result to a time trend effect, we introduce the time trend as an additional right-hand side variable. These results are reported in the fourth column of each panel. The addition of a time trend does not generally change the inference; where coefficient estimates are significant in the time trend's absence, they are significant in its presence.

V. Conclusion

Our results suggest that economy-wide and in the pharmaceutical and semiconductor industries individually, industry's use of inventors with past experience conducting university research, and of inventors with advanced degrees, has increased. This may mean that industry has increased its access to university-produced knowledge through the knowledge imbedded in inventors' human capital. That industry is making greater use of university-produced knowledge is also reflected in the citation data. Economy-wide and in the pharmaceutical and semiconductor industries individually we observe an increase in the citing of university patents. Using our inventor-based measures, we find a faster increase in access to university research in the semiconductor industry. Using the citation-based measure, we find roughly equivalent increases. The pharmaceutical industry shows greater access to university research (by any of our three measures) than the semiconductor industry.

In our firm-level analyses, we find larger firms are more likely to access university research than smaller ones. In general, firms with higher K/L ratios are more likely to utilize inventors on their patents who had previous university research experience and inventors with advanced degrees. Firms in both industries with more experienced inventors were more likely to produce patents that cited university research and were more likely to utilize inventors with university research experience. Younger pharmaceutical firms were more likely to utilize inventors with university research experience and to produce patents that cited university research.

We recognize a number of shortcomings in our analysis that we plan to remedy in future drafts. For example, our name matching procedure undoubtedly is subject to error, sometimes treating different inventors as a single inventor, and other times treating the same inventor as different inventors. Too many matches produced too many inventors showing university backgrounds; too few matches produced too few inventors with university backgrounds. These matching errors are likely more important in the analysis of levels of involvement with university research, as opposed to the analysis of trends. Nonetheless future drafts will include tests of the sensitivity of our findings to alternative matching rules. Also, because the dependent variables in our regression models are logit transformed, it is a difficult matter interpreting the coefficients. The next draft will use the coefficient estimates to derive marginal effects of the independent variables on proportions of patents that involve university-experienced inventors, for example. Finally, the next draft of the paper will investigate how the speed of diffusion has evolved over the period of our study, by measuring how the lag between the occurrence of university research and its reflection in industry innovation has changed.

An interesting question is how the use of university research affects the productivity of R&D in firms. In future work, we plan to explore how a firm's use of researchers with university experience affect its R&D productivity.

Appendix A. SOUNDEX coding system

A SOUNDEX code for a surname is an upper case letter followed by 6 digits. For example the SOUNDEX code for Kim is K500000, while that for Marschke is M620000. The first letter is always the first letter of the surname. The rules for generating a SOUNDEX code are:

1. Take the first letter of the surname and capitalize it.

2. Go through each of the following letters giving them numerical values from 1 to 6 if they are found in the Scoring Letter table (1 for B, F, P, V; 2 for C, G, J, K, Q, S, X, Z; 3 for D, T; 4 for L; 5 for M, N; 6 for R; 0 for Vowels, punctuation, H, W, Y).

3. Ignore any letter if it is not a scoring character. This means that all vowels as well as the letters h, y and w are ignored.

4. If the value of a scoring character is the same as the previous letter then ignore it. Thus if two ‘t’s come together in the middle of a name they are treated exactly the same as a single ‘t’ or a single ‘d’. If they are separated by another non-scoring character then the same score can follow in the final code. The name PETTIT is P330. The second ‘T’ is ignored but the third one is not since a nonscoring ‘I’ intervenes.

5. Add the number onto the end of the SOUNDEX code if it is not to be ignored.

6. Keep working through the name until you have created a code of 6 characters maximum.

7. If you come to the end of the name before you reach 6 characters, pad out the end of the code with zeros.

8. Optionally you can ignore a possessive prefix such as ‘Von’ or ‘Des’.

See "Using the Census SOUNDEX," General Information Leaflet 55 (Washington, DC: National Archives and Records Administration, 1995) for the detailed method.

Appendix B. Number of Patent Applications

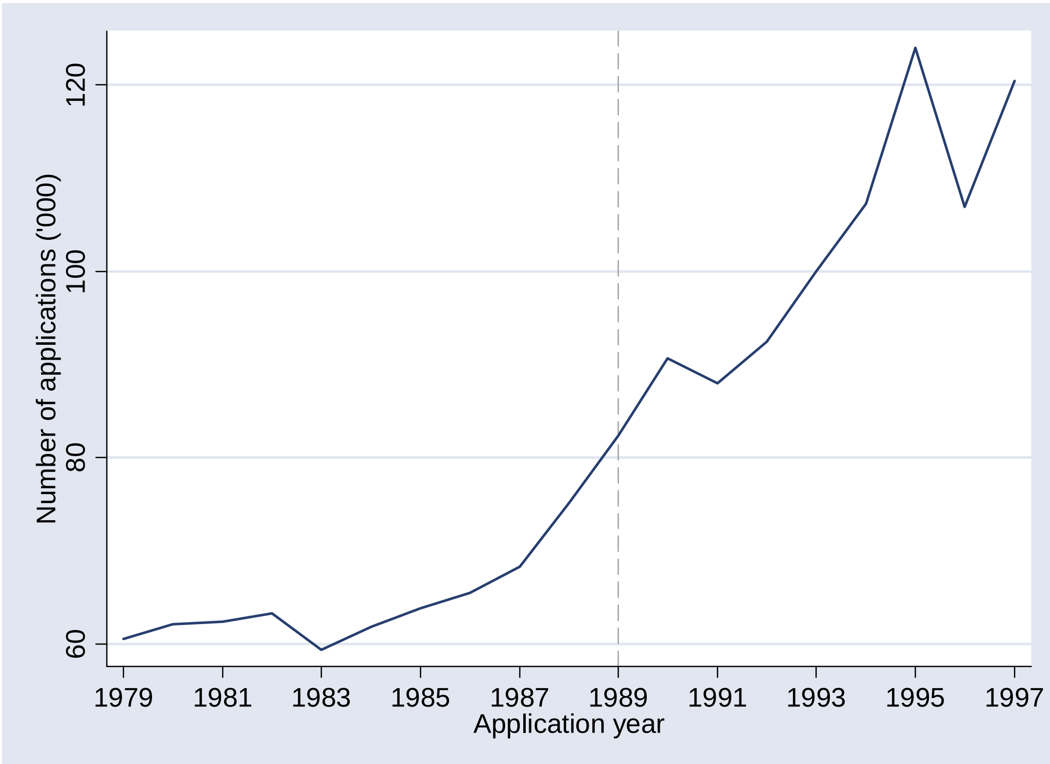

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Figure 1 Patents by Inventors with University Patent Experience

A. All Industries

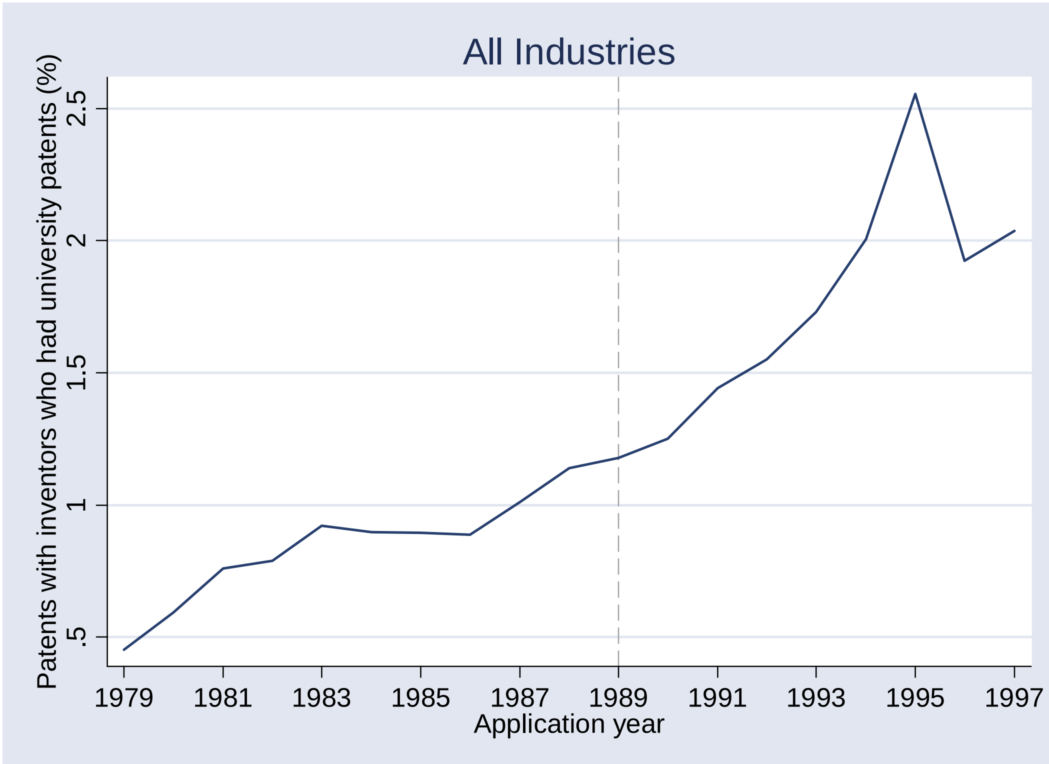
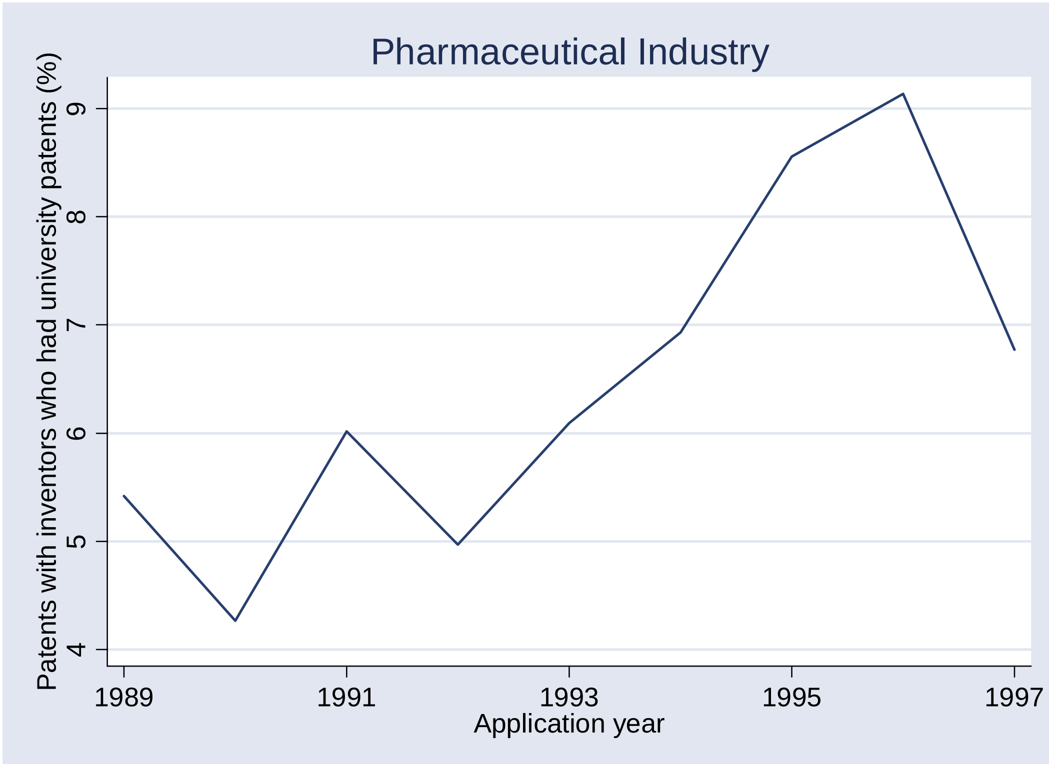


Figure 1 (continued)

B. Pharmaceutical Industry



C. Semiconductor Industry

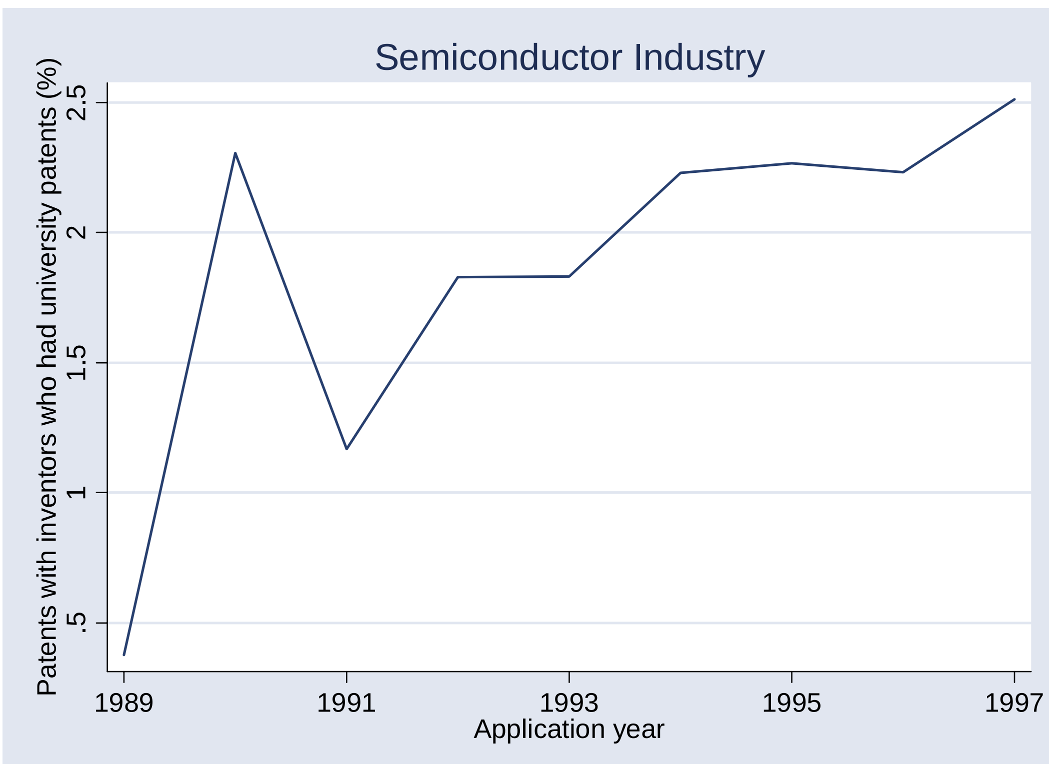


Figure 2 Patents by Inventors with Advanced Degrees

A. All Industries

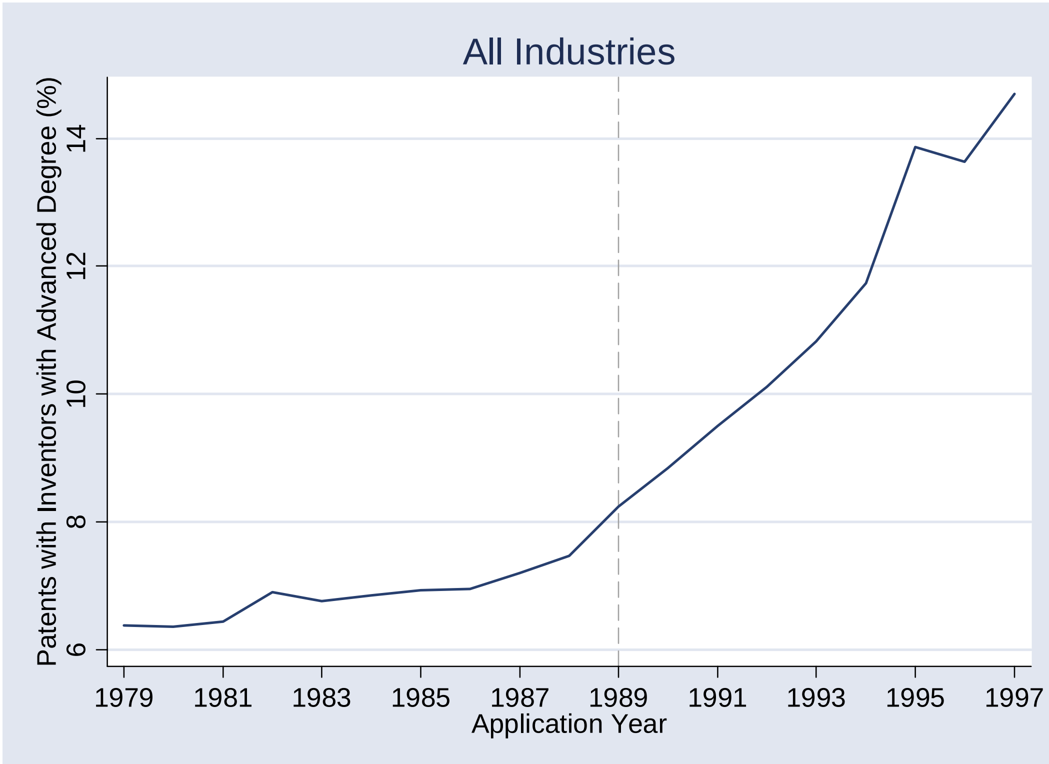
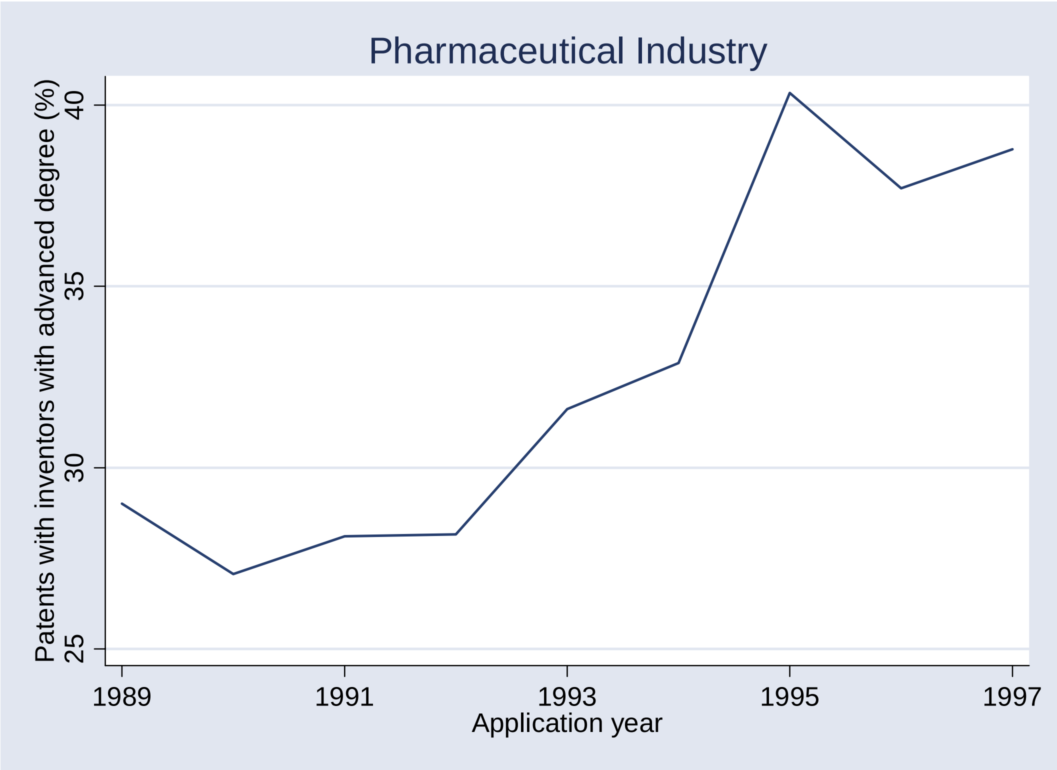


Figure 2 (continued)

B. Pharmaceutical Industry



C. Semiconductor Industry

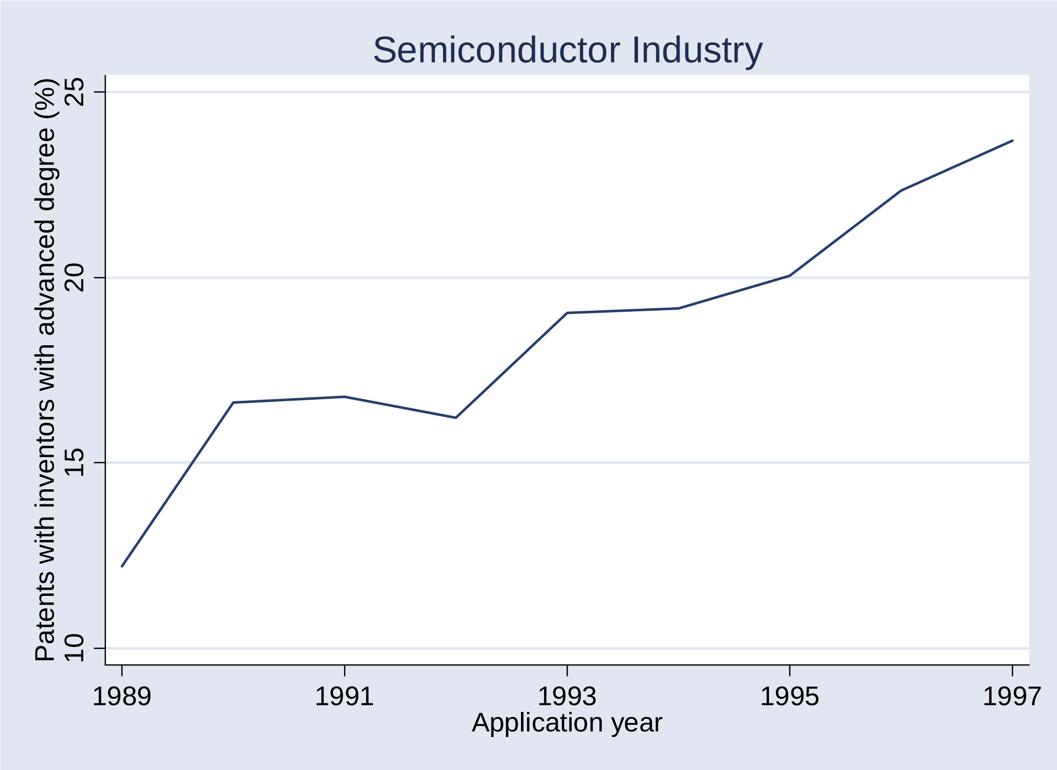
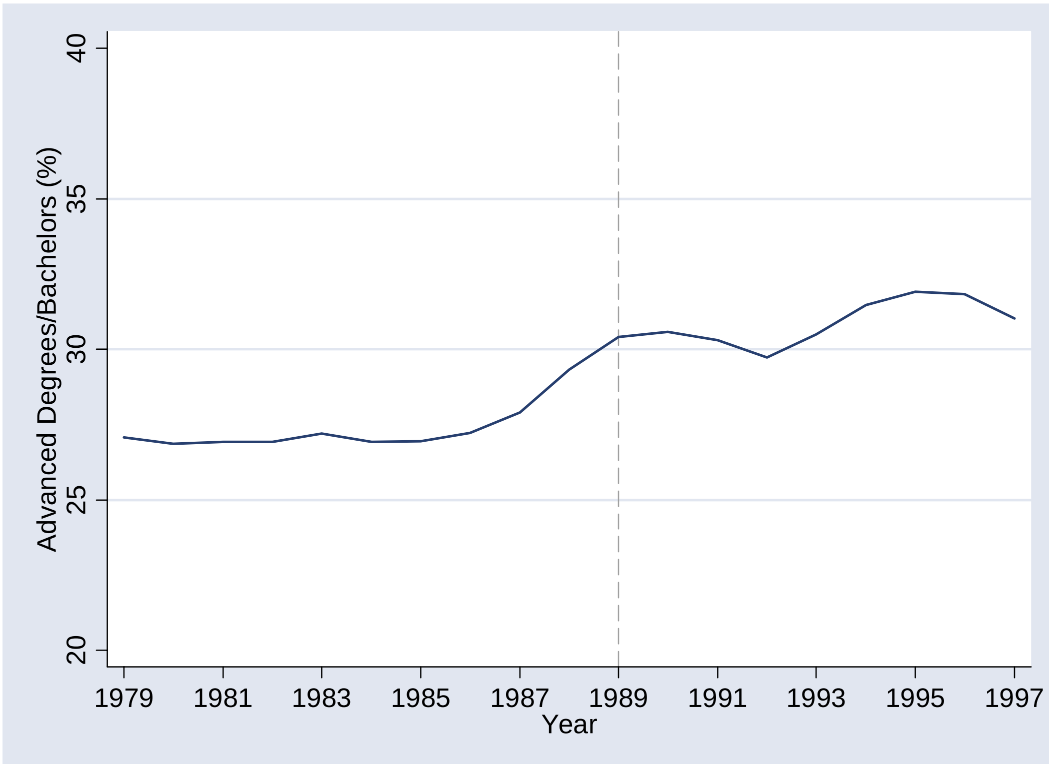


Figure 2 (continued)

D. Graduates with Advance Degrees



Source: National Science Foundation, Division of Science Resources Statistics, *Science and Engineering Degrees: 1966-2001*, NSF 04-311, (Arlington, VA 2004).

Figure 3 Patents with Citations to University Patents

A. All Industries

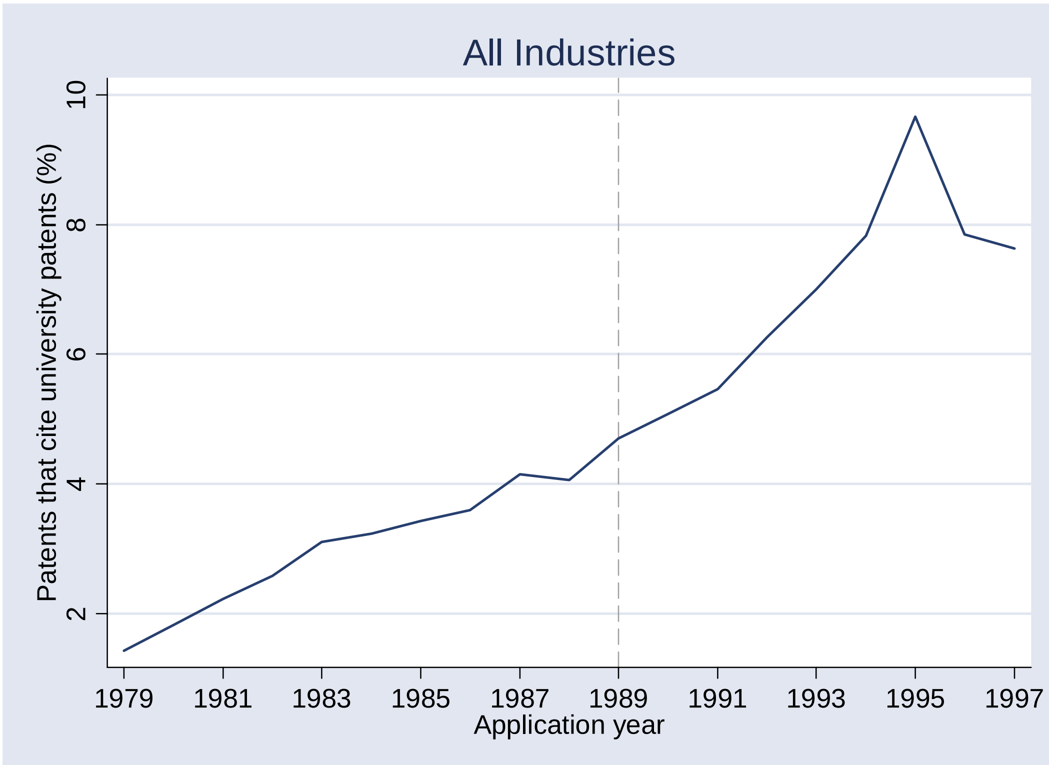
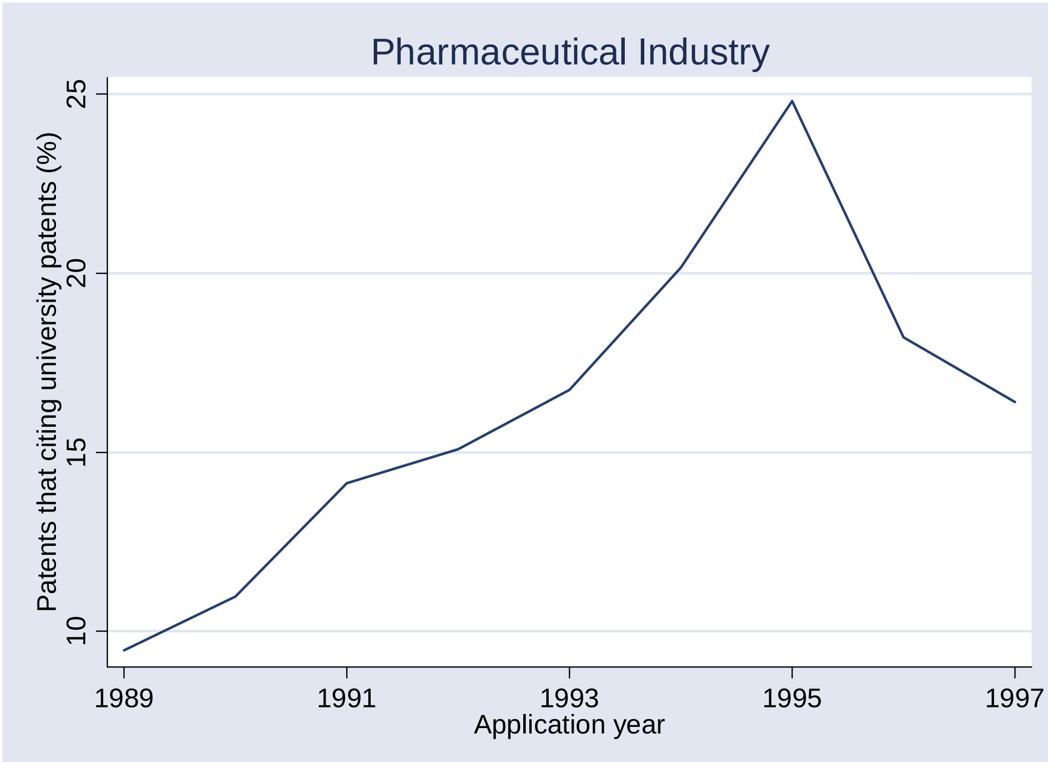


Figure 3 (continued)

B. Pharmaceutical Industry



C. Semiconductor Industry

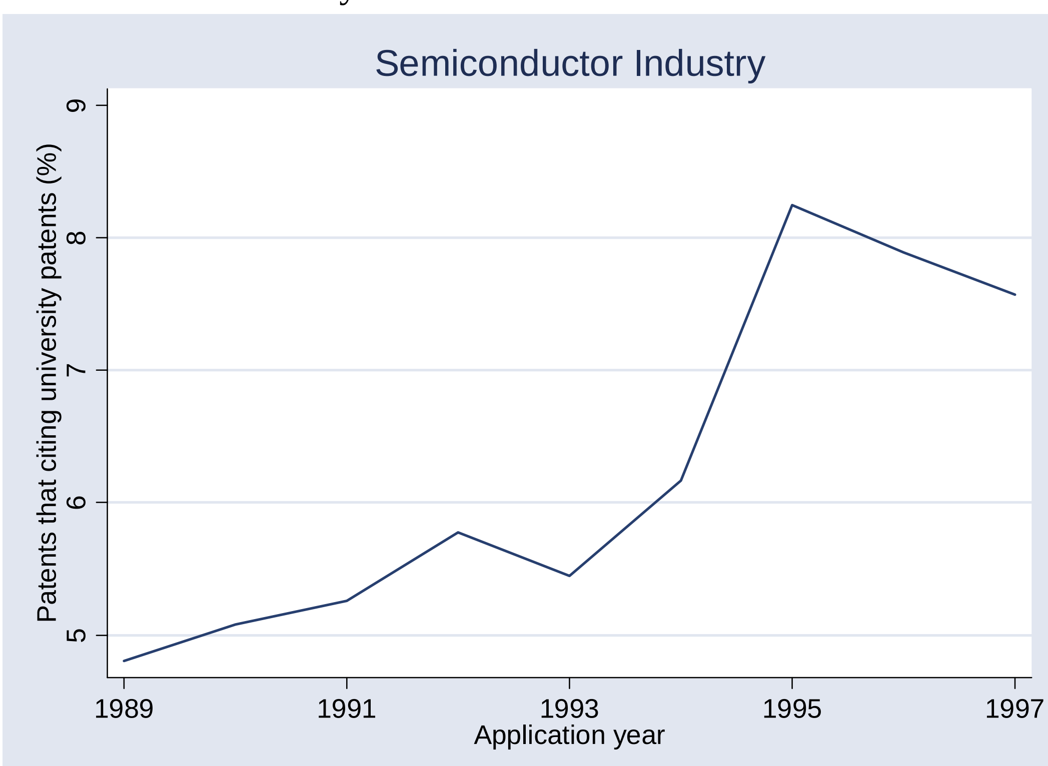


Table 1. Variable Definition and Sample Statistics

	Definition	Mean (Standard Deviation)	
		Pharmaceutical	Semiconductor
UNIV	Fraction of patents that involve inventors who are university-affiliated	0.1287 (0.2632)	0.0344 (0.1458)
ADVDEG	Fraction of patents that have inventors on them who have advanced degrees	0.2988 (0.3277)	0.1707 (0.2597)
UCITE	Fraction of patents citing past university-assigned patents	0.3036 (0.3567)	0.0797 (0.1849)
EMPLOYEE	Number of Employees	9,046 (17,249)	4,508 (14,876)
R&D	Real R&D expenditures in 1996 constant dollars	2,098 (3,852)	693.3 (2,250)
K/L	Capital-labor ratio, or deflated plant and equipment over the number of employees	1.145 (6.663)	1.183 (7.313)
NSIC	Number of secondary SIC’s assigned to a firm	2.3456 (1.716)	1.702 (1.214)
MEXP	Median experience of all inventors in a firm	5.4796 (3.555)	4.550 (3.107)
FIRMAGE	Years elapsed since the founding year of a firm	29.88 (39.81)	19.50 (19.74)

Table 2 Determinants of Firm Use of Inventors with University Patenting Experience

Dependent variable = logit transform of UNIV

	Pharmaceutical				Semiconductor			
Log EMPLOYEE	0.4890		0.8341	0.9298	0.6290		0.6551	0.7332
	1.96		2.32	2.51	3.28		3.01	3.33
Log R&D		0.6109				0.5276		
		2.38				2.43		
Log K/L	0.0193	-0.0925	0.1410	0.0333	0.9179	0.7913	1.0489	0.7652
	0.05	-0.23	0.29	0.07	3.42	2.68	3.71	2.59
Log NSIC	0.5212	0.5419	0.4585	0.3701	0.5930	1.0599	0.7073	1.0347
	0.69	0.74	0.53	0.43	1.05	1.85	1.21	1.75
Log MEXP			3.3145	3.2587			1.0964	1.1000
			5.85	5.74			3.04	3.08
Log FIRMAGE			-1.7479	-1.9495			-0.3176	-0.6302
			-2.37	-2.56			-0.68	-1.31
Time trend				0.1617				0.3052
				1.11				3.15
Observations	626	626	500	500	576	576	556	556
R^2	0.0503	0.0790	0.1392	0.1348	0.1087	0.0837	0.1323	0.1490

Note: All models are estimated with random (firm) effects. Constant and dummies indicating zero values for R&D and the K/L ratio omitted from table.

Table 3 Determinants of Firm Use of Inventors with Advanced Degrees

Dependent variable = logit transform of ADVDEG

	Pharmaceutical				Semiconductor			
Log EMPLOYEE	0.7515 2.71		0.8094 2.01	1.0800 2.63	0.8293 2.55		0.8074 2.18	0.8755 2.39
Log R&D		1.2029 4.17				1.0916 3.07		
Log K/L	0.8391 1.87	0.5049 1.11	1.4851 2.70	1.1729 2.11	1.5843 3.76	1.1848 2.58	1.6115 3.60	1.3634 2.91
Log NSIC	0.0967 0.11	-0.0781 -0.09	-0.2768 -0.28	-0.5767 -0.59	0.0967 0.11	0.1672 0.19	0.1232 0.13	0.4367 0.46
Log MEXP			0.9054 1.41	0.7959 1.24			0.6362 1.13	0.6674 1.19
Log FIRMAGE			-0.9196 -1.11	-1.4448 -1.72			-0.2218 -0.28	-0.5996 -0.74
Time trend				0.4868 2.94				0.2664 1.76
Observations	626	626	500	500	576	576	556	556
R^2	0.0443	0.0847	0.0638	0.0720	0.0792	0.0793	0.0791	0.0945

Note: All models are estimated with random (firm) effects. Constant and dummies indicating zero values for R&D and the K/L ratio omitted from table.

Table 4 Determinants of Citations to University Patents

Dependent variable = logit transform of UCITE

	Pharmaceutical				Semiconductor			
Log EMPLOYEE	-0.1875		-0.0648	0.0525	0.8481		0.7842	0.9088
	-0.59		-0.14	0.11	2.93		2.43	2.85
Log R&D		0.0472				1.1122		
		0.14				3.52		
Log K/L	0.6267	0.4977	0.6385	0.4910	0.8498	0.4373	0.7302	0.1575
	1.14	0.88	0.94	0.72	2.28	1.07	1.89	0.39
Log NSIC	0.7339	0.4517	0.6990	0.5909	0.0657	0.2139	-0.2929	0.3553
	0.72	0.46	0.61	0.51	0.08	0.27	-0.36	0.44
Log MEXP			0.5771	0.5718			0.9613	0.9687
			0.72	0.71			1.95	2.00
Log FIRMAGE			-0.4806	-0.6867			0.6618	-0.0898
			-0.50	-0.71			0.94	-0.13
Time trend				0.2365				0.5568
				1.20				4.28
Observations	581	581	465	465	556	556	538	538
R^2	0.0056	0.0102	0.0151	0.0223	0.0811	0.0727	0.0831	0.1207

Note: All models are estimated with random (firm) effects. Constant and dummies indicating zero values for R&D and the K/L ratio omitted from table.