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Aggregate evidence of localized academic knowledge transfer in the U.S.

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Abstract

Technology transfer and, more broadly, knowledge spillover from universities to industry has become increasingly studied as universities have become charged with driving local economic growth. This study offers several empirical improvements over prior efforts to measure the aggregate local effects of academic research. It uses counts of scientific publications and citations as more direct measures of academic knowledge than R&D spending. It makes use of panel data with greater breadth and depth: the sample covers all 105 U.S. metropolitan areas with significant academic research and spans 22 years. The positive local geographic association between university research and private-sector patenting found in prior studies is reaffirmed. There is some indication that this relationship strengthened in the last quarter of the sample, 1994-1999, suggesting that academic research was becoming more important to innovation in the 1990s. However, the volume of academic research was not found to have an effect on the rate of citations received by patents.

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1. Introduction

This study focuses on local academic knowledge transfer, that is, transmission of knowledge from universities to firms at sub-national levels. University to firm knowledge transfer has become increasingly important as the share of US basic research done by private firms has fallen in recent decades (Scotchmer and Maurer, 2004). As universities expanded their administration of technology transfer efforts following the Bayh-Dole act of 1980, the model of public-private research partnership has been increasingly important in fields such as medicine, pharmaceuticals, chemicals and electronics.[1] While there is extensive micro-evidence regarding the mechanisms and process of technology transfer (see Mowery, Nelson, Sampat and Ziedonis, 2004, for an overview), there are only a handful of studies that quantify the aggregate local relationship between academic research and industrial innovation in the US.

The empirical approach of this paper is to model the flow of knowledge as the effect of academic research in an innovation production function estimated over some level of geographic aggregation. This approach has previously been employed with data from the US by Jaffe (1989), Acs, Audretch and Feldman (1992), Anselin, Varga and Acs (1997, 2000) and Agrawal and Cockburn (2003), among others. More recent work from Europe that finds a geographic relationship between university research and industry innovation includes Fritsch and Slavtchev (2007), Abramovsky, Harrison and Simpson (2007), D'Este and Iammarino (2010), and Muscio, Quaglione and Scarpinato (2012). Though the estimated effect of academic research on private innovation in geographically aggregated studies without an experimental or quasi-experimental design cannot be taken as a causal effect, such estimates are valuable as descriptive associations that are suggestive of the causal mechanisms at work for the transmission of knowledge from universities to industry. One potential channel for transfer is formal technology licensing by university faculty and staff. Still, more knowledge is transferred than just what is appropriated by its university originators – spillovers of knowledge into the public domain. To the extent that new knowledge is tacit, that is, not able to be completely communicated through writing, knowledge transmission will be localized. An advantage of the geographic production function approach, as opposed to studying citation patterns or surveying firms and technology managers, is that it does not require precise measurement of every channel, as the end result of all knowledge exchange within a geographic area should be evident in greater rates of innovation.

There has been substantial ambiguity in the literature on university-industry technology transfer over what constitutes a "spillover" (Breschi and Lissoni, 2001). This ambiguity may have arisen because the use of academic discoveries by industry has more facets than the phenomenon of R&D spillovers between firms, which has been more extensively studied in economics. While the primary mechanism for inter-firm spillovers is labor-market turnover (Arrow, 1962), academic knowledge transfer occurs through multiple channels, some of which are true spillovers, in terms of not being appropriable, and others not. In the case of the patenting and licensing of well-defined innovations, universities and faculty are able to appropriate some of the returns to their discoveries, but in other cases knowledge flows freely through other channels.[2] Survey evidence reported in Cohen, Nelson and Walsh (2002) shows that corporate R&D managers more often consider channels such as informal interaction, consulting and recent hires to be important to their research activities

[1] The Bayh-Dole act gave universities property rights to innovations resulting from Federally-funded research.
[2] An interesting related question is whether protection of intellectual property hinders the free flow of knowledge, but this is beyond the scope of this paper. Murray and Stern (2007) provide convincing evidence that it does.

than channels such as licenses and contract research. This is supported by Agrawal and Henderson (2002), who reported that MIT faculty rated university patents, licenses and research collaboration as less important than consulting and recent graduates in transmitting discoveries to industry. In both surveys, publishing was the most highly regarded channel. D'Este and Patel (2007), with a survey of academic researchers in the UK, confirmed that consulting and meetings are important channels of knowledge transfer, but also found joint research, training and the creation of new physical facilities to be more frequent activities of academics than patenting, licensing and starting firms. Given the scope and frequency of these informal channels of knowledge transfer, the proportion of spilled knowledge in total commercially valuable knowledge generated by universities is probably high.

Knowledge spillover has been identified as a factor critical to economic growth (e.g., Romer, 1990; Grossman and Helpman, 1991) and also for agglomeration economies and the growth of cities (Glaeser, Kallal, Scheinkman and Schleifer, 1992). The localization of knowledge spillover has become an important policy concern for the U.S. as international competitiveness has moved alongside national security as reasons for the federal support of R&D (Freeman and Van Reenen, 2009). However, there is evidence that the tendency of inventors to cite patents produced within their own country more frequently and quickly than those from abroad has been declining since 1990 (Griffith, Lee and Van Reenen, 2011).

A comparison of the studies that investigate academic knowledge transfer with geographic innovation production functions reveals the strengths and weaknesses of their approaches. The pioneering study was Jaffe (1989), which made use of panel data on 29 U.S. states over 1972-77, 1979 and 1981. Using a three stage least squares instrumental variable approach, he estimated a direct elasticity of corporate patents with respect to academic R&D of 0.1.[3] The interquartile elasticities for the areas of Drugs, Chemicals and Electronics ranged between 0.08 and 0.30. Anselin et al (1997) used a cross-sectional dataset covering 125 U.S. metropolitan areas in 1982. They used a count of innovations identified by the U.S. Small Business Administration. In their most completely specified model the estimated elasticity of innovations with respect to academic R&D was 0.093, which was remarkably close to Jaffe's finding. Further, they find a weaker but still statistically significant effect of university research conducted in counties adjacent to metropolitan areas, suggesting the effects of university research weaken with distance from the center of a metropolitan area. Their follow-on study (Anselin et al, 2000) revealed that the effect of academic R&D is substantial for certain technical areas only, such as electronics and instruments. Agrawal and Cockburn (2003) examine the correlation between academic publishing and private-sector patenting across US and Canadian metropolitan areas over the period 1991-1997, for three narrow sub-fields of electrical engineering. They found strong positive correlations and a high degree of geographic co-location, after controlling for employment in professional, scientific and technical occupations. Further, the presence of an "anchor tenant", a firm performing a large amount of internal R&D, was found to greatly increase such correlation. Fritsch and Slavtchev (2007) use a panel that covers patenting in German districts over 1995-2000; in their model specifications they find elasticities of private sector patent applications with respect to externally-sourced academic R&D of 0.017 – 0.035.

Many other studies have been conducted on local academic knowledge spillovers in Europe, see Fritsch and Slavtchev (2007) for a review. Several recent ones stand out due to the novelty of their methods. Abramovsky et al (2007) found that R&D conducting establishments tended to locate close to high-quality research departments, at the postal-code level in the UK. D'Este and Iammarino (2010) found that the frequency of collaboration by

[3] Taking into account that academic R&D may induce firms to locate R&D activities near universities, the total indirect effect was a much larger elasticity of 0.6.

engineering faculty in the UK decreases with the distance to the collaborating firm; also that the frequency of collaboration is positively related to the research quality score of a faculty member's department. With Italian data, Muscio et al (2012) found that proximity to industrial districts strengthened the level of private R&D funding that academic departments received, after controlling for other relevant factors.

Of the US studies only Jaffe (1989) makes use of panel data, but not at the metropolitan level. Only Agrawal and Cockburn (2003) use publications as a measure of academic knowledge, and not for all areas of science and technology. The present study is able to shed more light on the empirical question of academic knowledge transfer in the US due to its broad coverage (described in the next section) and its use of academic outputs as measures of knowledge.

2. Empirical Method and Data

The empirical models employed here are of geographic innovation production functions in the style of Pakes and Griliches (1984) and Jaffe (1989), where corporate innovation is a function of corporate R&D and an academic input. Observations are taken on metropolitan areas (i) in years (t). Due to the discrete count nature of patent data, negative binomial models of the following form are estimated:

$$I_{i,t} = e^{(\beta_0+\beta_1 k_{i,t}+\boldsymbol{X}'_{i,t}\varphi+\boldsymbol{\alpha}_i+\boldsymbol{\eta}_t)} + \varepsilon_{i,t} \tag{1}$$

Here, *I* represents private-sector product or component innovation, *k* is a measure of academic knowledge, and *X* is a vector of time-varying control variables, such as corporate R&D and scientific employment. Since the primary measure of *I* is a count of patents accumulated over time, *I* is assumed to have a Poisson distribution. Metropolitan-area indicators, $\boldsymbol{\alpha_i}$, are included in some specifications to control for other time-invariant characteristics of metropolitan areas. Year effects, $\boldsymbol{\eta_t}$ **,** are included in all specifications to control for annual variation in the number of patents. In most specifications log-transformations of the regressors are used. Error terms are clustered by metropolitan area for estimates of equation (1), which accounts for correlation in patenting over time within metropolitan areas.

Model (1) controls for time-invariant factors but is not a fixed-effect negative binomial model, as originally described by Hausmann, Hall and Griliches (1984). Conditional fixed-effect negative binomial models of the following form were also estimated:

$$I_{i,t} = [e^{(\beta_0+\beta_1 k_{i,t}+\boldsymbol{X}'_{i,t}\varphi+\boldsymbol{\eta}_t)}]\boldsymbol{\alpha}_i + \varepsilon_{i,t} \tag{2}$$

This model allows the variance of the underlying Poisson dispersion parameter to differ across metropolitan-area groups. A drawback when estimating this model, however, was that it was not possible to cluster the error terms.

Data for a panel covering 105 U.S. metropolitan areas and spanning 1977 to 1999 were collected from several different sources. The main dependent variable, *I*, is measured as the count of patents assigned to U.S. corporations in the year that their application was filed. Data on patent counts was obtained from the National Bureau of Economic Research (NBER) patent dataset, as detailed in Hall, Jaffe and Trajtenberg (2001). Patents assigned to US businesses and indicating a US residence of the first inventor were used; I assigned them geographically by the county of the city of the first inventor, the counties being assigned uniquely to metropolitan areas. Any patents in counties outside of included metropolitan areas were ignored.

Patents can be problematic as a measure of innovation because they vary widely in their value. For example, Scherer and Harhoff (2000) found that the percent of value in the top 10% of patents ranged between 81-85% in different samples of U.S. and German patents. In the present analysis, with a sample mean of 258 patents per observation, there are likely to be valuable patents in most metropolitan areas. However, it is unknown whether the measured increase in patents related to academic research is in high-value patents. In some specifications an alternative measure of innovation was used: the patent citation rate. This measure was the average number of citations to the patents generated in a particular metropolitan area and year and was available in the NBER patent dataset. Use of this measure required shortening the panel as it would have been truncated in the latter third of the panel due to the long lag (8 years, on average) between patent application date and citation by other patents.

Publication counts, and the counts of the number of citations that these articles received from other publications, serve as measures of the scientific knowledge variable, *k*. These I collected for 218 U.S. research universities and medical schools, 98 non-profit research institutes and 5 federally funded research and development centers.[4] This set of institutions included those that received at least $10 million in federal research grants in 2003. Publications outside the natural sciences and engineering were not included.

While the effects of academic research are of primary interest here, most research and development activity in the U.S. (75%) is performed by private firms (Scotchmer and Maurer, 2004). However, the location and quantity of private R&D is largely kept secret for strategic reasons, so direct controls for private R&D at the metropolitan area level are not available. I created an approximate measure of private R&D from two sources: the *Survey of Industrial Research and Development* (SIRD) from the National Science Foundation (NSF), and the Census Bureau's *County Business Patterns* (CBP). The SIRD provided state-level figures for private R&D, however in many cases state totals were suppressed. For these, I imputed the values by allocating the difference between the total R&D reported for a region and the R&D reported for states within that region to the suppressed observations based on the share of population of the suppressed states. The CBP provided total payroll earnings for each county, which were aggregated to metropolitan areas by counties. Each state's R&D was apportioned to the metro areas within each state based on each metro area's share of its state's payroll earnings to create the control variable Industry R&D. This variable is undoubtedly measured with error, since state R&D totals are distributed by the size of each metropolitan area's economy, without regard to its R&D intensity. However, using it is better than simply not controlling for industry R&D. The CBP also recorded employment in scientific and engineering services, which was aggregated to the metro level to create another control variable for industrial R&D activity. These two controls have a correlation of 0.61. In the following analysis the two-year moving average of each variable, using the current year and a one-year lag, was generally used, to account for the possibility of a lag time between the innovation inputs and the time of patent application.[5]

Only metropolitan areas with least one of the universities or research institutes for which publication data was collected were included in the sample. I used the Census Bureau's 2002 definition of Metropolitan Statistical Areas (MSA) to define metropolitan areas, but in some cases used Core-Based Statistical Areas (CBSA), which consist of several

[4] All articles authored by faculty of those institutions were obtained from automated searches on the Thompson ISI *Web of Science* in 2006, using a Perl script written by a research assistant. Further details regarding the construction of the panel are available upon request from the author.
[5] The results were not sensitive to the choice of lag.

contiguous Metropolitan Statistical Areas.[6] Using CBSA instead of MSA for large metropolitan areas is intended to capture knowledge spillover within an observation, under the assumption that people tend to interact more often with others in the same greater metropolitan areas. Table I provides summary statistics for the variables in the main metropolitan/year panel. As can be seen by comparing the medians and means in Table I, all of the variables have distributions that are right-skewed: much innovative activity is concentrated in a minority of metropolitan areas.

Table I: Sample statistics - Panel with 2146 metropolitan area/year observations

Variable	Mean	Median	Min.	Max.	Source
Corporate patents	258.1	55.0	0.0	8934.0	NBER
Academic publications	1464.4	751.0	0.0	18127.0	Web of Science
Citations to academic pubs.	48057.3	18042.0	0.0	775727.0	Web of Science
Employment in scientific services	6250.4	2079.0	10.0	101582.0	Census CBP
Estimate of private R&D, $m	240.5	51.7	0.0	9345.3	NSF & CBP

3. Results

Regression estimates of models fitting metropolitan-level counts of patents with measures of academic knowledge, private R&D, and year effects are shown in Table II. Each of these regressions fits a Negative Binomial model by Maximum Likelihood estimation.[7] In using the log of the two-year moving average of each of the regressors I dropped observations for which the two-year moving average of any variable was zero valued, resulting in the panel of 2,146 observations. The elasticity of private-sector patents to university publications estimated in the first model, column (1), is 0.31. It could be biased upwards from omission of controls for metropolitan size and employment density, the latter of which was found to be a critical determinant of patenting by Carlino, Chatterjee and Hunt, (2007). With the inclusion of metro indicators in column (2), the estimated elasticity is 0.10. This effect is marginally statistically significant; against a one-sided alternative hypothesis, it is statistically significant at under 10%.[8] The control variables have robust effects as should be expected: the elasticity of patents with respect to corporate R&D is 0.16 and with respect to employment in scientific services is 0.24. An alternative specification in column (3) shows estimates of the conditional fixed-effects model. The estimated elasticity of patents with respect to publications was also 0.10, indistinguishable from the model with metropolitan-area indicators.

The model was then re-estimated using publication citation counts instead of publication counts. In columns (4) and (5) I find their effect to be lower: an elasticity of 0.24 in column (4), but only 0.055 with metro fixed-effects in column (5), which is indistinguishable from zero. Again the elasticity estimated with the conditional fixed-effects model in column (6) was nearly the same, at 0.056, and statistically significant owing to the independently distributed errors. It is interesting that the effect of citations is lower than that

[6] In a few cases, I modified the official MSA or CBSA to include neighboring counties or MSA, if such counties had a population center and were not part of another MSA or CBSA.
[7] Use of the Negative Binomial instead of the Poisson is appropriate when the data have an overdispersed Poisson distribution. Likelihood-ratio test statistic values on the over-dispersion parameter, obtained for models (1) and (2) of Table II, were significant at the 1% level, indicating over-dispersion. Refer to Gutierrez, Carter and Drukker (2001) for details on the modified likelihood-ratio test appropriate in this context.
[8] This result is obtained with error terms clustered by metropolitan area. Under the classical assumption of independently and identically distributed errors, the p-value for the usual two-sided test is 0.005.

of publications. It could be that the citation count, a quality measure, is not related to the number of patents, but more highly correlated with the quality of those patents.

Table II: Negative Binomial regressions of patents on academic publications, controls.

Dependent variable: patents	(1)	(2)	(3)	(4)	(5)	(6)
log(publications)	0.3053***	0.1035	0.1028***			
	(0.0770)	(0.0752)	(0.0260)			
log(pub. citations)				0.2409***	0.0551	0.0558***
				(0.0678)	(0.0591)	(0.0194)
log(R&D spending)	0.3934***	0.1612***	0.1833***	0.3794***	0.1634***	0.1828***
	(0.0865)	(0.0483)	(0.0178)	(0.0878)	(0.0484)	(0.0178)
log(sci. employment)	0.4504***	0.2408***	0.1581***	0.4649***	0.2453***	0.1705***
	(0.0958)	(0.0847)	(0.0261)	(0.0956)	(0.0840)	(0.0260)
Constant	-2.4908***	0.0835	0.0789	-2.8267***	0.1197	0.1429
	(0.5578)	(0.7914)	(0.2167)	(0.6357)	(0.8473)	(0.2232)
Log-likelihood	-11,567.92	-9,448.54	-8,879.79	-11,574.98	-9,450.51	-8,883.78
Metropolitan dummy variables?	N	Y	N	N	Y	N
Conditional fixed-effects model?	N	N	Y	N	N	Y
Error terms clustered by metro?	Y	Y	N	Y	Y	N
n =	2,146	2,146	2,146	2,146	2,146	2,146

* significant at 10%, ** significant at 5%, *** significant at 1%

Standard errors in parentheses

All regressions include year effects.

All regressors are two-year moving averages.

It is possible that the effect of academic research on private patenting may have been changing over the 22 year span of the panel. Industry's share of federal R&D funding was falling in the 1990s while the share to universities was rising, according to Scotchmer and Maurer (2004, fig. 8.3). In Table III the models are re-estimated with the inclusion of a variable for the interaction between an indicator for late-sample years (1994-1999) and the two-year moving average of log(publications) or log(pub citations). From the estimated coefficients of these variables the elasticities appear to strengthen modestly in the latter sample, by 0.02 to 0.025, but whether the effect strengthened at all depends on the choice of model; when clustered errors are used, no significant difference is observed.

Also interesting is the question of whether the quality of private-sector patents was determined by the volume of academic research. I created a proxy variable for the quality of patents, patent citations per patent, using information on the number of patents citing each private sector patent from the NBER patent dataset. Negative binomial regressions of this variable would not converge, however, so double-log models were estimated by Ordinary Least Squares instead. Since the available patent data ended in 2001 and there is a considerable lag between when patents are applied for and when they are cited by other patents, the sample is limited to 1977-1994. These estimates are shown in Table IV. Although there is a measurable effect of the volume of academic papers on the patent citation rate in column (1), this is knocked out by the inclusion of metropolitan-area fixed effects in column (2). Similar results are found using publication citations in columns (3) and (4). It appears from this analysis that neither the volume of academic research nor the degree of academic citation has an aggregate effect on the forward citation rate of private-sector patents.

Table III: Negative Binomial regressions with late-sample interaction

Dependent variable: patents

Variable	(1)	(2)	(3)	(4)
log(publications)	0.1131	0.1023***		
	(0.0753)	(0.0259)		
1994-99 indicator * log(publications)	0.0250	0.0205**		
	(0.0394)	(0.0104)		
log(R&D spending)	0.1574***	0.1795***	0.1587***	0.1778***
	(0.0463)	(0.0178)	(0.0469)	(0.0178)
log(sci. employment)	0.2419***	0.1587***	0.2476***	0.1716***
	(0.0842)	(0.0261)	(0.0832)	(0.0260)
log(pub. citations)			0.0614	0.0545***
			(0.0589)	(0.0194)
1994-99 indicator * log(pub. citations)			0.0250	0.0201**
			(0.0307)	(0.0084)
Constant	-0.1166	-0.0564	-0.1624	-0.0402
	(0.8531)	(0.2278)	(0.8998)	(0.2368)
Metropolitan dummy variables?	Y	N	Y	N
Conditional fixed-effects model?	N	Y	N	Y
Error terms clustered by metro?	Y	N	Y	N
Log-likelihood	-9,446.90	-8,877.85	-9,448.00	-8,880.92
n =	2,146	2,146	2,146	2,146

* significant at 10%, ** significant at 5%, *** significant at 1%

Standard errors in parentheses

All regressions include year effects.

All regressors are two-year moving averages.

4. Conclusions and Avenues for Future Research

The economic and social benefits of research in science and engineering have been increasingly scrutinized in the past decade. For example, the National Science Foundation initiated the *Science of Science and Innovation Policy* (SciSIP) program in 2005 to encourage the study of the innovation impacts of science. Since 1980, most research universities have established offices of technology transfer and are engaged in licensing university inventions to and partnering with private firms. Yet only a handful of studies have looked at the geographically localized aggregate effects of academic research in the U.S. This study is the first to use panel data covering all U.S metropolitan areas that have a substantial academic research presence and the first to extend for more than two decades. It is also the first panel study to make use of publications as a measure of academic research instead of academic R&D spending, an input.

Despite the differences in empirical approach, the scale of the effect of academic research on private-sector patenting estimated here is very similar to the aggregate effects measured by the prior studies of Jaffe (1989), Anselin et al (1997) and Agrawal and Cockburn (2003). Further, there is some evidence, although it depends on the choice of modeling assumptions, that the spillover effect strengthened in the 1990s. This is entirely consistent with the increase in university technology transfer efforts that were occurring at the time and the growing encouragement of faculty to be engaged in consulting and start-up activity. It may also have reflected a decline in basic research conducted by private-sector labs.

Table IV: OLS Regressions of patent citation rate.

Dependent variable:	log(pat. cites/patent))			
	(1)	(2)	(3)	(4)
log(publications)	0.0772***	-0.0385		
	(0.0226)	(0.0888)		
log(pub. citations)			0.0697***	-0.0783
			(0.0182)	(0.0602)
log(R&D spending)	0.0200	0.0429	0.0160	0.0469
	(0.0217)	(0.0341)	(0.0211)	(0.0339)
log(sci. employment)	0.0139	0.0377	0.0118	0.0430
	(0.0309)	(0.0669)	(0.0308)	(0.0679)
Constant	1.4696***	1.2115***	1.3249***	1.4953***
	(0.2083)	(0.4160)	(0.2153)	(0.4487)
Metro fixed effects?	N	Y	N	Y
R-squared	0.17	0.41	0.18	0.41
n =	1,702	1,702	1,702	1,702

* significant at 10%, ** significant at 5%, *** significant at 1%

Errors clustered by metropolitan area

Robust standard errors in parentheses.

Increases in patenting do not imply increases in valuable innovations, however. It may have been that the marginal patents represented ideas and inventions that never made it to the market, or had little impact if they did. The analysis of the patent citation rate done here supports this view. No connection was found between the volume of academic research and the impact of private patents on subsequent patenting. However, the panel I used for that analysis ended in 1994. It is possible that more recent data may uncover a relationship between academic research and the rate that patents are cited by other patents.

Also of interest is whether geographically localized aggregate knowledge spillovers strengthened into the 2000s. Extending the panel used in this study to the present is not possible, but extension to 2011 may soon be possible. The Patent Data Project of the National Bureau of Economic Research has made U.S. patent data available in a usable form through 2006. Data on publications indexed by Web of Knowledge are obtainable to the present. Private R&D and employment in scientific services data are publicly available, although as of this writing, have only been compiled in usable form to 1999 by this author.

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