The Anchor Tenant Hypothesis: Exploring the Role of Large, Local, R&D-Intensive Firms in Regional Innovation Systems

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Abstract

We examine the geographic co-location of university research and industrial R&D in three technology areas. While we find strong evidence of co-location of these vertically connected activities, regional economies appear to vary markedly in their ability to convert local academic research into local commercial innovation. We develop and test the hypothesis that the presence of a large, local, R&D–intensive firm - an anchor tenant - enhances the regional innovation system such that local university research is more likely to be absorbed by and to stimulate local industrial R&D.

Keywords: regional innovation systems, university technology transfer, spillovers, absorptive capacity

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1 Introduction

The relationships between innovation, productivity, growth, and geography continue to attract much attention. Regional variation in productivity and growth related to the innovation process has important implications for public policy as well as private investment decisions, but its causes remain imperfectly understood. One important factor appears to be the role of universities as sources of research spillovers. As academic and industrial research interests have converged in areas such as computer science, electrical engineering, and biotechnology, it has become clear that university research plays a key role in regional innovation performance.

In this paper, we explore a set of questions concerning the relationship between university research and industrial R&D within regions. To what extent are university research and, separately, industrial R&D, concentrated in specific technology areas? To what extent are they co-located? To what degree do regions vary in their productivity as measured by the industrial-R&D-to-university-research ratio? What might explain this variation?

We begin by examining the degree to which university research and, separately, industrial R&D associated with certain technical areas are concentrated. We do this for three narrow technology areas in electrical engineering: medical imaging, neural networks, and signal processing.[1] We find strong evidence of geographic concentration of both university research

[1] Medical imaging technology facilitates the noninvasive generation of internal body images by employing techniques such as magnetic resonance imaging, ultrasound, nuclear medicine, and X-ray computed tomography. Neural networks are a form of multiprocessor computer systems based on collections of mathematical models that emulate some of the observed properties of biological nervous systems and draw on the analogies of adaptive biological learning. Signal processing technology enables the processing (e.g., filtering, compression, decompression) of signals (e.g., an analog electrical voltage or current, the digital output from the readout system of a compact disc player) and is used in a wide variety of applications such as mobile phones, multimedia computers, video recorders, hard-disc drive controllers, and modems.

and industrial R&D in these technologies.[2]

We then explore the degree to which university research and commercial activity are co-located. Anecdotal evidence suggests that local innovation systems play a very important role in commercializing academic research, and our results suggest that these upstream-downstream activities are indeed co-located to a considerable extent. Our measures of academic research activity in these three technologies are strongly correlated at the regional level with measures of downstream industrial R&D activity, even after controlling for variation in the economic size of geographic units. However, despite the positive correlation between measures of these activities, we also note that there is significant variation across regions in the relationship between them. One interpretation of this variation is that regions differ in their productivity in converting local upstream university research into local downstream industrial R&D activity. In the context of this interpretation, the productivity of local innovation systems varies quite substantially, and, as the primary objective of the paper, we explore one hypothesis that may explain a significant portion of the variation. This is the "anchor tenant" hypothesis, to which we now turn.

2 The Anchor Tenant Hypothesis

The classic "anchor tenant" is the large department store in a retail shopping mall that creates demand externalities for the other shops. Large department stores with a recognized name generate mall traffic that indirectly increases the sales of lesser-known stores. Pashigian and

[2] In a related paper, we also test for agglomeration, in the sense of "excess concentration" as discussed by Ellison and Glaeser (1997), in each of the three technology areas for both university research and industrial R&D (Agrawal and Cockburn, 2002). The results are inconclusive.

Gould (1998) examined the degree to which mall developers internalize these externalities by offering rent subsidies to anchor tenants and charging rent premiums to other mall tenants.

In our regional, hi-tech context, we define an anchor tenant as a large, locally present firm that is: 1) heavily engaged in R&D in general and 2) has at least minor absorptive capacity in a particular technological area, such as medical imaging. By virtue of its participation in local markets for technology and specialized inputs, such a firm may confer significant externalities upon smaller innovative firms. These externalities may facilitate entry by smaller firms seeking to utilize university research, lower their costs, and improve their prospects for future profitability and growth. More – and more efficient – activity by this "fringe" of smaller firms increases the impact of vertical knowledge spillovers in the local economy, above and beyond the direct consumption of local academic research by the anchor tenant.[3]

Our specific hypothesis, therefore, is that the presence of an anchor tenant firm enhances the regional innovation system such that local university research is more likely to be absorbed by and to stimulate local industrial R&D. This effect is in addition to any role of the anchor tenant as a direct consumer or supporter of university research. Furthermore, the ability of anchor tenants to do this is a function of their particular characteristics: large, local, and R&D-oriented, with absorptive capacity in a particular technology area.

[3]The reader may be concerned about the endogeneity associated with the presence of anchor tenants and the productivity of regional innovation systems. In other words, the presence of anchor tenants may be correlated with or even be the result of productive regional innovation systems rather than a determinant of them. This is a legitimate concern. In our analysis here, we assume that the geographic distribution of these very large R&D–oriented firms is exogenous. Absent good instruments for regional innovative productivity, we cannot easily test for this empirically. We do, however, attempt to control for other factors affecting innovation in the region, such as the size of the "professional, scientific, and technical" labor force as well as the overall level of industrial R&D in the region. Also, there is anecdotal evidence that the type of firms that we have classified as anchor tenants have been in their locations for quite a long time and have, at least to some extent, shaped the regional innovation system in which they are situated. However, the endogeneity issue remains a concern and will be the focus of future research.

Why do these characteristics matter? First, consider the requirement that an anchor tenant be R&D-oriented and have some absorptive capacity in a particular technology area. For any given technology, the degree to which the presence of an anchor tenant affects the efficiency of vertical knowledge transfer will depend on the extent to which the anchor tenant participates in relevant markets. Large firms that are not engaged in R&D are unlikely to have a significant impact on markets for R&D inputs or technology-intensive products. Unless they have some involvement in a particular technology, even highly R&D-intensive firms are unlikely to have a major impact on markets which are specific to that technology. For example, the presence of a pharmaceutical firm in a region is unlikely to stimulate the local supply of workers with skills specific to signal processing, nor is such a firm likely to be a potential licensor of signal processing innovations made by local firms.

Second, anchor tenants must be large firms. This makes them likely to be large, direct consumers of university research; but above and beyond this, their size may have important indirect effects. Anchor tenants may increase "deal flow" through the technology transfer process and thus provide support for the specialized institutions required to affect technology transfer from universities to industry. Absent this concentrated volume of transactions with a sophisticated and demanding customer, universities may find it difficult to maintain a large technology transfer office or may not fully develop necessary resources and expertise.

Anchor tenants also may have an important indirect role in stimulating both the supply and demand sides of relevant markets off campus. The volume of their transactions in local markets for R&D inputs and outputs may have a significant impact on liquidity, pricing efficiency, and related transaction costs. The thickness of local markets for ideas and the factors of production relevant to commercializing university research may play an important role in determining the economic viability of smaller firms. Furthermore, by virtue of their size, anchor tenants are likely to enjoy traditional Schumpeterian economies of scale and scope. The marginal cost of adding an additional research or development project is often less for a larger firm since it is more likely to be able to spread specialized skills and equipment over multiple projects. Also, given the inherent uncertainty over the nature of the new product, R&D projects are less risky for larger firms since they have access to a greater range of existing products and markets that may be related. These scale and scope economies may have important *qualitative* implications for the impact of anchor tenants on local markets.

On the supply side, large anchor tenant firms thicken factor markets differently than many small firms that equal the size of the anchor tenant in aggregate. Economies of scale and scope allow large firms to employ workers with highly specialized skills such as experience in large-scale manufacturing, in taking firms public, and in entering foreign markets. The presence of workers with these skills in local labor markets may make these skills available to smaller firms. Similarly, large firms attract high-quality suppliers of ancillary products and services. These may be technology-related, such as repair and maintenance of scientific instrumentation, or business-related, such as patent lawyers or financial intermediaries. In either case, without an anchor tenant, these suppliers may be absent or of lower quality. Thus an anchor tenant may stimulate supply of high quality scarce inputs, making the local economy much better at absorbing, finding markets for, raising capital for, and developing early-stage innovations.

On the demand side, the impact of demand from large firms on “intermediate” markets for early-stage technologies may be quite different from the aggregate demand of many smaller firms. Large firms may be better informed about final demand in distant markets. By possessing high-capacity manufacturing capabilities or established distribution channels, large firms may be able to profitably manufacture and sell products which small firms cannot. By selling into many different markets, large firms may have access to information that suggests new applications for an early-stage technology of which smaller firms are unaware.

Third, to have a significant impact on technology transfer within a region, an anchor tenant must have a local presence. This is because the externalities generated by the anchor derive to a great extent from geographic proximity of the “fringe” of smaller firms. On the supply side, many of the externalities generated by large firms are geographically concentrated. Labor markets, for example, may be thickened at a regional level. Consider the case of a manager at a large firm who is considering leaving the anchor tenant in order to join a smaller firm developing a new technology. Given the transactions costs of moving, if faced with a choice between two otherwise identically attractive employment opportunities at a local small firm versus a distant small firm, the manager is more likely to move to the local firm.

On the demand side, markets for technology products and services stimulated by large firms are likely to function more efficiently where transactions take place within the local economy. This is due to the important role of tacit knowledge in such transactions. The transfer of tacit knowledge occurs most efficiently through direct personal interaction. Therefore, firms that wish to supply the anchor tenant with technology products that involve tacit knowledge transfer have an advantage if they are located in the same region.

3 Literature

While most of the economic concepts, such as economies of scale and scope, upon which the anchor tenant hypothesis is built are well understood, the notions of absorptive capacity, the localization of knowledge spillovers, and the role of tacit knowledge in university knowledge transfer are perhaps less common. Therefore, we briefly review some of the key papers on these topics.

First, a variety of studies have sought to explain the variance in ability of firms to utilize knowledge spillovers. These studies focus on firms' R&D investments, their "connectedness" to outside scientists, and their location, relative to the sources of spillovers. For example, Cohen and Levinthal (1989, 1990) introduce the concept of "absorptive capacity" and argue that a firm's ability to utilize spillovers is a function of its own investment in R&D. We draw from this idea in the construction of our anchor tenant concept. Cockburn and Henderson (1998) build on the notion of absorptive capacity, but add that the degree to which firms are "connected" to scientists outside the firm is also important for utilizing knowledge spillovers. Lim (2000) restructures the above two concepts and argues that absorptive capacity is primarily a function of connectedness, of which investment in in-house R&D is just one of several components. Zucker *et al.* (1998) further explore the utilization of knowledge spillovers, but emphasize the role of geography. They investigate the importance of connectedness to firms by examining their location decisions relative to star university scientists.

Second, a large body of research (see Feldman, 1994 and Feldman, 1999) has established that there is a significant degree of geographic localization of knowledge spillovers. Among recent studies, Jaffe *et al.* (1993) find a positive and significant relationship between "original patents" and "patents that cite the original patents" at the MSA level, Audretsch and Feldman (1996) find a positive relationship between "local university research funding" and "local industry value-added" at the state level, and Branstetter (2000) identifies a relationship between "scientific publications from the University of California" and "patents that cite those papers," also at the the state level.

Finally, the channels through which knowledge is passed from universities to firms have been investigated from a number of perspectives. Understanding the channels through which knowledge spillovers occur is important for this study, since different channels have different implications for the effects of geographic proximity. For example, knowledge that is transferred through the publication channel is much less sensitive to geography than knowledge that is tacit and passed through a direct two-way communication channel, such as conversation. Cohen *et al.* (1998) and Cohen *et al.* (2002) examine the relative importance of the complete set of university-industry transfer channels from the perspective of the knowledge recipient, namely firms. They find that transfer channels that favor geographic proximity, such as conversations and consulting, are at least as important to firms as channels that are reasonably independent of proximity, namely publishing and patenting. In comparison, Agrawal and Henderson (2002) analyze the relative importance of transfer channels from the perspective of the knowledge creator, namely professors. Similar to Cohen *et al.*, they find professors believe that channels that are geographically sensitive are at least as important as those that are not. Jensen and Thursby (1998), Colyvas *et al.* (2002), and Agrawal (2002) all identify the importance of tacit knowledge transfer channels, which are sensitive to proximity, by examining the degree to which university inventions are so early-stage that they require the cooperation of the inventor to develop.

4 Variables and Data

For this study, we collected data on indicators of academic research activity and industrial R&D as well as a variety of control variables for the 268 US MSAs and consolidated metropolitan statistical areas (CMSAs) and the 25 Canadian census metropolitan areas (CMAs) - hereinafter collectively referred to as the "MSAs."[4] We removed 39 MSAs since their level of both academic and industrial electrical engineering research is *de minimis*, resulting in a working sample of 254 local economies.[5]

[4] While MSAs and CMAs are similar in spirit, they are defined slightly differently. The Canadian criterion requires that the urban core have a population of at least 100,000 for a metropolitan area to exist. In contrast, for the period 1990 to 2000, the United States had two criteria to determine whether or not a metropolitan area existed. In the United States, a metropolitan area exists where there is either a city of 50,000 or more inhabitants or a Census Bureau defined urban area, i.e., a population of at least 50,000 and a total metropolitan population of at least 100,000 (75,000 in New England). Thus, the Canadian approach is the more restrictive of the two.

[5] Specifically, MSAs were dropped from the sample if they had both fewer than five publications in IEEE journals per million inhabitants and fewer than 20 patents in electrical engineering per million inhabitants.

4.1 Industrial R&D (Patents)

We use patent counts to measure industrial R&D.[6] Patent counts are generated by first creating a list of all patents that contain at least one US classification from a set of classifications associated with a particular technological area (e.g., medical imaging). The sets of US classifications used were created in consultation with electrical engineering professors who work on the technologies under investigation.[7] We include patents that have application dates between 1991 and 1997, inclusive. Patents are then assigned to MSAs by the address of the first inventor. It is important to note that the inventor MSA is often different from the assignee MSA. For example, many patents assigned to IBM Corp. in New York are invented by scientists and engineers located at labs in other MSAs. For our purposes, we are interested in identifying the location where the research actually occurred, and thus we use inventor MSAs.

There are three areas of concern associated with this measure of industrial R&D. First, not all industrial R&D results in patents. In fact, it has been well documented that for strategic reasons, many innovations generated from industrial R&D are protected by trade secret, other forms of intellectual property, or are not protected at all due to short product life cycles or difficulties associated with patenting (Cohen *et al.*, 2000). Historically, this has been particularly true for software (or software-like) inventions, though there has been a substantial increase in the propensity to patent software and related technologies during the period under investigation.

[6]The data used to generate this metric were purchased from the United States Patent and Trademark Office (USPTO), www.uspto.gov.

[7]The set of classifications associated with each technology is available from the authors by request.

Second, there is noise generated by our use of the classification system. US patent classifications do not exactly match the technology areas we are investigating. Most patents are assigned multiple classifications as their application spans several areas. However, the invention may be more related to some areas for which it is classified than others. As a result, the data suffers from both false positive and false negative results. In other words, the data contain patents that are not directly related to the technology under investigation, and the data are missing patents that should be included.

Third, patents are a very "noisy" measure of R&D outcomes, in the sense that not all patents represent the same level of economic importance. The distribution of the economic value of patents is highly skewed (see Pakes, 1986), which likely reflects a similar high degree of heterogeneity in their technological significance. Quality-weighting patent counts could minimize the impact of errors in measuring innovative output, but reliable measures of quality are difficult to find. One possibility would be to use citation-weighted patent counts, but citations are only weakly associated with patent quality and using them would add further complexity to the econometric model.

To evaluate the seriousness of these concerns, we consider the degree of systematic bias by MSA that we might expect on any of these dimensions. For example, might some MSAs have a lower propensity to patent their industrial innovations than others? It is certainly possible. For example, MSAs that have a notably high propensity towards software development, such as Seattle and San Francisco, might patent less than average per unit of R&D expenditure. Similarly, to the extent that narrowly defined areas of technology are geographically clustered, if a technology area is misclassified in our system, false positive and false negative observations may not be distributed across MSAs randomly. The direction of potential bias in terms of measuring the relationship between university research and industrial R&D or in testing the anchor tenant hypothesis is not obvious. However, we plan to investigate the nature and magnitude of these potential sources of bias in future research. In the meantime, we interpret our results with caution.

4.2 University Research (Publications)

We use publication counts to measure university research activity. Specifically, we use author-MSA counts based on articles by university-based authors in particular journals. For example, to measure university research activity in the area of medical imaging, we begin by generating a list of all articles that appeared in the journal *IEEE Transactions on Medical Imaging* during the period 1991-1997. Then, we increment the MSA counter for the state associated with each university-based author. So, a paper by two authors – one from Boston-Worcester-Lawrence and one from Washington-Baltimore – will increment both the Boston and Washington counters by one. Also, each author is categorized by type: public, private, or university. Only university authors increment the MSA counters when measuring university research.

There are five areas of concern associated with this measure of university research. First, not all research is published. Agrawal and Henderson (2002) report that MIT electrical and mechanical engineering professors estimate that just less than 20% of the new knowledge generated by research at their labs that is utilized by industry is passed through the publishing channel. Other important channels of knowledge transfer include consulting, recruiting graduate students, research collaborations, and to a lesser extent, conferences, informal conversations, and patenting. Cohen *et al.* (1998) report that only 20% of U.S. manufacturing firms consider university publishing to be an important knowledge transfer channel for their industry. Thus, it clearly seems that publishing only represents a fraction of overall university research output. In addition, it is possible that professors in some regions are more likely to publish their research than others. For example, it might be the case that some regions have, on average, higher-quality engineering departments that attract faculty members who are more publishing-oriented than their colleagues elsewhere. However, given the importance of publications as a universal metric for research performance, we do not expect this discrepancy to be too large. Still, we note this issue as a concern that begs further research.

Second, not all published research on a particular technology is contained in the journals included in our analysis. For example, only a fraction of articles associated with medical imaging are published in the journal *IEEE Transactions on Medical Imaging.* Many other journals publish articles relevant to medical imaging. This is quickly verified by examining the citations in articles published in *IEEE Transactions on Medical Imaging*, which include references to dozens of other journals. We consulted two electrical engineering professors regarding which journals we should include in our analysis. We selected journals based on two criteria: 1) the journal is considered amongst the top journals that publish research on the topic under study and 2) all the articles included in the journal are related to the topic under study. We feel reasonably confident that the journals selected for this study fulfill these criteria. However, we are still concerned that certain factors, such as the location of journal editors during the period under study, introduce bias in terms of the frequency of articles that are published from particular regions. Still, we do not expect that the location of journal editors will be correlated with the location of industrial activity in that technological area, nor that the location of journal editors will be correlated with the location of anchor tenants.

Third, not all articles represent the same quality of research. Some articles are obviously more important than others and result from higher-quality research or longer-term projects. However, there seem to be plausible constraints on the degree to which the quality of articles by university researchers could vary systematically across MSAs. The editorial function of the journal should control for this, at least to some degree. Still, one could argue that top-ranked engineering departments are clustered in a small number of regions, that research quality is highly correlated with department ranking, that journals accept papers that fall within a certain quality range, and thus that the quality of research published in a particular journal does indeed vary (within the range allowable by the particular publication) systematically by region. The electrical engineering professors we consulted with indicated that they do not believe this to be the case with the journals we examine in this study. However, in future research we plan to examine this further by weighting papers by citation to control for publication "quality."

Fourth, articles vary in the degree to which they are relevant for industrial application. Since the measure of university activity is being compared to a measure of industrial activity, the variance in applicability is relevant. University departments do sometimes tip towards a majority of either basic or applied research; therefore, there is legitimate concern regarding the relationship between geography and the degree to which research is basic rather than applied. However, we suspect that this problem is constrained by the editorial guidelines of the journals from which this data is generated, since we specifically selected journals that focus on applied research.

Finally, the author-MSA metric may cause concern. For example, consider the case of two articles of identical quality, where one has a single author in Boston and the other has two coauthors in Boston. The first paper will increment the Boston paper counter by one, whereas the second paper will increment the Boston paper counter by two. So, coauthored papers have a greater influence on the research metric than single-authored papers. We count each author separately because we consider each to be an independent point of access to the tacit knowledge associated with that research. An alternative measure might be to only count first authors. This way, each paper would contribute equal weight. However, this would not reflect the degree to which coauthors facilitate increased access to and dissemination of tacit knowledge to local industry. In terms of bias relevant to this study, it is not obvious that the propensity to coauthor papers would vary systematically across regions. However, to the extent that this might be the case, we leave its investigation for future research.

The data used to generate this metric is collected from the Institute for Scientific Information's (ISI) *Science Citation Index*. Data is collected from the journals *IEEE Transactions on Medical Imaging, IEEE Transactions on Neural Networks, and IEEE Transactions on Signal Processing* for analyses of medical imaging, neural networks, and signal processing, respectively. All articles from these journals that were published between the years 1991 through 1997, inclusive, are included in the analysis.

4.3 Anchor Tenants

As described above, we define an anchor tenant for a particular MSA and technology (e.g., Boston, medical imaging) as a firm that meets two conditions. First, the firm must have some absorptive capacity in the particular technology area. This is measured by the presence of at least one patent granted to the firm from the set of specified US patent classifications during the period under investigation (1991-1997 inclusive). Second, the firm must demonstrate that it is heavily involved in R&D in general. This is measured by the presence of at least one thousand patents granted to the firm, with any US patent classification, during the period under investigation. (We find similar results when this threshold is reduced to 500 patents.) A firm that meets both of these conditions is considered an anchor tenant.

For example, Texas Instruments, Inc. is an anchor tenant in the Dallas-Fort Worth metropolitan area in the technological areas of signal processing and neural networks. It satisfies the two conditions described above because it has conducted a great deal of R&D in general and at least some on signal processing and neural networks specifically. However, the same firm is not an anchor tenant in medical imaging as it has not conducted any R&D (by our measure) in this area and thus has no absorptive capacity related to this technology. Also, since our analysis is at the research facility level, it is possible for firms to be anchor tenants in multiple locations. For example, Motorola, Inc. is an anchor tenant in signal processing in both the Chicago-Gary-Kenosha and the Phoenix-Mesa metropolitan areas.

The idea of the "anchor tenant" effect is illustrated in a stylized fashion by four "matched pairs" of MSAs in Table I. These pairs of MSAs are similar in terms of size (population) and university research in the area of medical imaging (publications). However, their commercial R&D as measured by patents varies considerably. For example, the Los Angeles MSA is similar to the New York MSA in size and level of university research in medical imaging, but the New York MSA has two anchor tenants (IBM and Lucent) while Los Angeles has none in this technology area; New York has approximately double the number of industry patents as L.A. Similarly, the San Francisco and Boston MSAs are similar in size and level of university research in medical imaging, but San Francisco has two anchor tenants (Sun and HP) while Boston has none; again, the MSA with an anchor tenant has substantially more industry patents. The same pattern holds when comparing Minneapolis (3M) with Atlanta and Pittsburgh with Rochester (Eastman Kodak).

It is important to note that while the anchor tenant may play an important role in stimulating industrial research, that firm is not necessarily responsible for the majority of industrial research on that topic in the MSA under investigation. For example, Table II illustrates that the two anchor tenants in the New York MSA are only responsible for two of that region's 43 industrial patents in medical imaging. Similarly, Table III illustrates that the anchor tenant in the Minneapolis MSA is responsible for only three of that area's 15 industrial patents. When we test the anchor tenant hypothesis, we remove patents by the anchor tenant such that only the patenting activity of the "fringe" is measured. The empirical analysis is described in detail below.

4.4 Control Variables

A variety of MSA-level control variables are used throughout the analysis. These include population, personal income per capita, professional-scientific-technical services, general electrical engineering patents, general electrical engineering papers, all patents, and all papers from journals included in the ISI's Science Citation Index. Population data are from the U.S. Bureau of the Census[8] and Statistics Canada.[9] Personal income per capita and professional-scientific-technical services are also both from the Census Bureau[10] and Statistics Canada.[11] The Professional, Scientific, and Technical Services sector (sector 54) of the 1997 Economic Census covers establishments with payroll that specialize in performing professional, scientific, and technical activities for others. The Census Bureau states that "these activities require a high degree of expertise and training."

General electrical engineering patents are counted by including all US patents that have been designated international patent classifications within the set: G01-G12 or H01-H05. The general categories for these classifications are physics ("G") and electricity ("H"). General electrical engineering papers are counted by including all IEEE publications. The Institute for Electrical and Electronic Engineers (IEEE) is a non-profit, technical professional association. In 2002, the Institute had over 360,000 individual members in 150 countries, held over 300

[8]State and Metropolitan Area Data Book, 1997-98, Table B-1.

[9]1996 Census of Canada, Profile Data, Ottawa, Canada.

[10]Gaquin, Derdre A. and DeBrandt, Katherine A., eds. *2000 County and City Extra: Annual Metro, City, and County Data Book, Ninth Edition.* Lanham, MD: Bernan Press, 2000. Table C, page 807-887. Data from the 1997 United States Economic Census, U.S. Census Bureau.

[11]*Labour Force Historical Review* (Statistics Canada data table), 1999. "Employment by Census Metropolitan Area, 3 month moving average." (averaged over 12 months to generate 1997 estimate). Accessed with Beyond 20/20 Professional Browser.

major conferences per year, and claimed to produce 30% of the world's published literature in electrical engineering, computers, and control technology.[12]

4.5 Descriptive Statistics

Table IV reports the descriptive statistics for variables constructed from these sources for the set of MSAs in our sample.

While the range of the paper and patent counts in each technology area is quite large, their distribution is highly left-skewed. In medical imaging, 185 out 254 MSAs had no publications and 198 had no patents. Similarly, in signal processing, there were 154 MSAs with no publications and 108 with no patents, while in neural networks 158 MSAs were without papers and 187 without patents. Signal processing is significantly "larger" than the other two technologies, averaging almost three times more papers and eight times more patents per MSA.

As can be seen in the Table, MSAs vary considerably in size, with population ranging from just over 82,000 (Pine Bluff, AR) to almost 20 million (New York–Northern New Jersey–Long Island). Just under 9% of the MSAs in the sample are located in Canada. One measure of the technology-intensity of these local economies is the fraction of the population falling into the Professional, Scientific, and Technical (PST) category. PST workers averaged just under 2% of the population, with a maximum of 5% and a minimum of 0.3%. Another indicator is the volume of patenting. Patents issued to private-sector assignees in all technology classes averaged about 1000 per MSA, ranging from only one to more than 28,000. In per capita

[12] http://www.ieee.org/about/

terms, patents in classes ranged eight per thousand inhabitants to less than 0.007. Just over one-third of these patents were in electrical engineering.

5 Empirical Results

5.1 Geographical Concentration

Research activity in our three technology areas is not evenly dispersed across North America. In fact, counts of patents and papers in these areas are highly concentrated within a handful of MSAs. This concentration of activity can be seen in summary measures such as the four-MSA concentration ratio, analogous to the four-firm concentration ratio, "CR4." In each technology area, the top four MSAs by share of patenting activity account for about 42% of patents, and the four largest MSAs by publishing activity account for 24% of medical imaging papers, 27% of neural networks papers, and 27% of signal processing papers. A more broad-reaching measure of geographical concentration is the "locational Gini" coefficient, which measures the extent to which the distribution of activity across geographical units departs from a uniform allocation. Two versions of this measure are presented: the "raw" Gini coefficient, based on the share of each activity in total activity, and the "relative" Gini coefficient.[13] Table V reports the results of computing locational Gini coefficients for the paper and patent counts across MSAs.

The high values obtained for the raw Gini coefficient on paper counts by MSA indicate

[13] The locational Gini coefficient is reviewed in Krugman (1991) and Amiti (1998). The formula used here is $G_L \equiv \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}|x_i - x_j|}{4n(n-1)\bar{x_i}}$, where for counts of activity X_i in $i = 1 \ldots n$ regions, x_i in the raw Gini is $X_i/\sum_i X_i$, and $\frac{X_i/\sum_i X_i}{Z_i/\sum_i Z_i}$ when the Gini is calculated relative to a broader activity Z_i.

that academic research in all three technology areas is highly geographically concentrated. (If the activity is evenly distributed across geographical units, $G_L = 0$, while if all the activity is concentrated in a single geographical unit, $G_L \to 0.5$.) Interestingly, similar results are obtained when the Gini is recomputed relative to the distribution of total EE activity.[14] There are no substantive differences in the degree of geographic concentration across technologies or between papers and patents. The only markedly different results are obtained when we compare the distribution of general electrical engineering activity to that of the narrower technology areas, in both cases considering these measures relative to the distribution of general science and engineering activity. Publishing activity in the broader field of electrical engineering is somewhat less geographically concentrated and patenting activity is much less concentrated. Perhaps this is because the more narrowly defined technology areas delineate more specialized researchers who tend to co-locate due to more geographically mediated knowledge spillovers. This proposition is interesting as it suggests a relationship between the level of technical specificity and the importance of spillovers. We plan to investigate this further in future research.

5.2 Co-location of University Research and Industrial R&D

If our notion of vertical knowledge spillovers within localized innovation systems is correct, then a positive statistical relationship should exist between the level of university research and the level of industrial R&D in a given technological area across MSAs.

[14] The relatively large numbers of MSAs with no measured activity may be biasing these calculations, but deleting observations with zero counts reduced these coefficients by only a few percent.

One piece of evidence for co-location is the raw correlation between papers and patents across MSAs, which is quite high: 0.67 for medical imaging, 0.52 for neural networks, and 0.77 for signal processing (Table VI). These correlations are robust to the exclusion of outliers, and non-parametric measures of association derived from the cross-tabulation of counts show a positive and statistically significant relationship. But this measure confounds the effect of the size of the MSA on both variables, so a better descriptive parameter is the coefficient on papers in a regression of patents on to papers and a control for the size of the MSA.

Table VII gives results from regressing patents on to papers. The univariate regression results simply restate the correlation coefficients. But even when we control for size using PST LABOR, in each of the three technologies we get a positive and strongly significant coefficient on papers. The same result holds using various other size controls such as population or the total number of IEEE publications or electrical engineering patents originating from the MSA. Taken at face value, these results imply that there is a very strong co-location effect: local patents in a technological area are strongly associated with the presence of upstream academic science. Here and in the additional regressions reported below, we place no structural interpretation on the results. Though there are good reasons to believe that papers "cause" patents in the sense that downstream industrial R&D activity relies on upstream science, it is quite possible that causation runs in the opposite direction. We have not specified a production function technology for R&D nor made any assumptions about the behavior of actors in this process. Rather, the regressions are presented as descriptive analyses of reduced form associations in the data.

These OLS regressions are estimated using a simple linear functional form; given the disparity in size over the sample of MSAs, there is likely to be a significant amount of heteroscedasticity. White's test statistic confirms this hypothesis, rejecting the null of i.i.d. errors at $P > 0.0001$. The presence of many zeroes in both the dependent variable and the main explanatory variable prevents us from using a log-log specification, which would be less vulnerable to this problem. We therefore re-estimated some equations using weighted least squares to account for heteroscedasticity under the assumption that the variance of the error term is inversely proportional to population. This has a relatively small impact on the standard errors relative to the unweighted regressions.[15]

One important source of specification error arises from the measurement properties of the dependent variables in these regressions. As counts of patents, these variables take on only non-negative integer values, suggesting that a Poisson-type model is appropriate. The functional form is

$$E[PATENTS] = exp(\alpha + \beta PAPERS) \tag{1}$$

Note that since PAPERS is zero for many observations, it is not possible to estimate the standard log-log functional form, and β cannot therefore be read directly as an elasticity. As in the OLS regressions, we again find a positive and strongly significant coefficient on PAPERS in all three technologies. However, this is driven largely by confounding with the size of MSAs; when ln(PST LABOR) is included in the regression, the PAPERS variable is knocked out. Moreover, these data are badly over-dispersed relative to the Poisson distribution: the χ^2

[15]However, computing robust standard errors using Stata's Huber-White estimator resulted in substantial increases, suggesting that the linear model is seriously misspecified.

goodness-of-fit statistic is very large in all cases, rejecting the null of $mean = variance$ at $P > 0.0001$.

One option for addressing over-dispersion is to use negative binomial regression, effectively adding a random effect to the model. While the coefficient estimates that results from this are broadly similar, the standard errors increase by an order of magnitude. Using this specification, PAPERS is only significant for the case of signal processing. However, a closer look at the data suggests that the negative binomial model may not be appropriate either. The large number of zero patent counts suggests an alternative reason why the $mean = variance$ property of the Poisson distribution is violated here; many MSAs appear to have no activity in these technology areas and therefore cannot be expected to generate patents.[16] If this is the case, then a different model is appropriate.

Here we use the ZIP ("Zero-Inflated Poisson") model proposed by Lambert (1992).[17] In this model, there are two unobserved states of the world, Regime 1 and Regime 2. In Regime 1, counts greater than zero are very rarely observed, while in Regime 2, counts are generated by a standard Poisson process in which zeroes can occur, but counts of one or more are also likely to be observed. The joint density of the data therefore has two distinct components: a standard Poisson equation giving the probability of observing counts conditional upon being in Regime 2, and a "Zero-inflation" equation giving the probability of being in Regime 1 or Regime 2. The "Zero-inflation" equation can be modeled as logit or probit. Two sets of

[16]The reader may question how this can be, given that 39 MSAs were omitted from the data at the outset because of their *de minimis* level of research. These 39 MSAs were removed because little electrical engineering research of any kind was conducted there. However, there remain MSAs in the data set where electrical engineering research did occur in general, but not in the particular technologies under investigation.

[17]See also Greene, 1994, and 2003 pp. 750-751 and 779-780.

coefficients are estimated by maximum likelihood, one for the covariates in the Poisson part of the model and one for the logit/probit "Zero-inflation" equation.

Results from estimating the ZIP model are presented in Table VIII. In each case, the "Zero-inflation" equation is assumed to be logit, with ln(population), share of EE in total patents, and a dummy for NO IEEE PAPERS as explanatory variables. The ZIP model jointly estimates the parameters of the logit regime model and the Poisson count model; the coefficients below the "Zero-inflation" subtitle are for the former while those above are for the latter. In two out of three technologies, we again find a positive and significant coefficient on papers.

5.3 The Anchor Tenant Hypothesis

Even after controlling for size, there is significant dispersion about the regression line of patents on papers. (For an example, see Figure 1.) One way to interpret this dispersion is in terms of the regional innovation systems' ability to convert local science into local industrial innovation. Substantial variation in the patent/paper ratio, even after controlling for size, suggests that other characteristics of MSAs may be important determinants of the productivity of local innovation systems. Indeed, our core hypothesis in this study is that the presence of anchor tenants is a significant factor driving productivity. A simple test of this hypothesis is to include a measure of anchor tenants in the regressions of patents on to papers.

Results for the OLS model are presented in Table IX. The measure of the presence of anchor tenants is ANCHORS, an indicator variable which equals one when there is at least one anchor tenant in the MSA. Essentially similar results are obtained using a direct count of anchor tenants instead of a dummy variable. As before, we control for the size of the MSA with PST LABOR and use weighted least squares to control for heteroscedasticity. Note that patents assigned to anchor firms are netted out from the dependent variable, so that the model should be thought of as referring to the relationship between university research and the patenting of "fringe" firms, or non-anchor companies.[18]

The results are striking: in all three technology areas, the coefficient on the interaction term is positive and strongly significant. For medical imaging and signal processing in MSAs which have an anchor tenant, the coefficient on PAPERS is roughly two to three times larger. For neural networks, the coefficient on PAPERS goes from negative and weakly significant to positive and significant when an anchor tenant is present.

The same flavor of results is obtained from estimating Poisson and Negative Binomial versions of this model, though, as argued above, there is reason to believe that these two models are misspecified. Our preferred specification is the ZIP model (see Table X), and here we find positive and strongly significant effects of the presence of anchor tenants. The impact is considerable: at the mean, the marginal impact of one more paper on the expected number of patents in medical imaging is 1.55 times larger in the presence of an anchor tenant, 2.7 times larger in neural networks, and 1.64 times larger in signal processing.[19]

[18]Anchor firms account for a varying fraction of total patenting in each technology and MSA. On average, this fraction is quite small (about 2%), but in a small number of MSAs it is much larger (over 90%). Netting out patents by anchor firms is important to avoid inducing a spurious correlation between the dependent variable and the anchor variable, but, as can be seen in the correlations reported in Table VI, the two counts are effectively very similar.

[19]Marginal effects were computed using Stata's numerical derivative-based *mfx* procedure, which computes the impact of a unit change in an explanatory variable upon the predicted value of the dependent variable. Magnitudes of marginal effects were compared for the cases where the anchor tenant dummy is set to zero

Though the test statistic proposed by Vuong (1989) favors the zero-inflated model over the standard Poisson for all three technologies ($Pr > Z = 0.054$ for medical imaging, $Pr > Z = 0.003$ for signal processing, and $Pr > Z = 0.029$ for neural networks), this model does not fully "soak up" the over-dispersion in these data. Robust standard errors were significantly larger, driving most of the coefficients in the Poisson part of the model into marginal significance, or insignificance, and in the negative binomial version of the ZIP model implemented by Stata[20] the estimated over-dispersion parameter is significantly different from zero in all three cases, suggesting that there is substantial heterogeneity across MSAs that is not accounted for by the model as specified. Though the negative binomial ZIP models give qualitatively similar results, in the sense that the ANCHOR variable has a positive coefficient for all three technologies (but is only strongly significant for neural networks), other coefficients in these regressions are quite unstable and the fit in the χ^2 or pseudo-R^2 sense is markedly worse than for the Poisson regressions. Skepticism about whether the distributional assumption underlying the negative binomial models is appropriate leads us to favor the Poisson-based ZIP model, though we are cautious about placing too much reliance on these results until the nature of the unobserved heterogeneity is better understood.

6 Conclusions

Important connections between university research and industrial R&D exist, but these are subtle and quite difficult to capture empirically. Anecdotal evidence suggests an important

versus when it is set to one.

[20] *Stata Base Reference Manual, Vol. 4, Version 8*, pp. 336-338.

role for universities in generating clusters of innovative "spin-off' companies, although econometric evidence on the presence of localized knowledge spillovers from universities is mixed. The results reported by, for example, Jaffe (1989), Acs, Audretsch, and Feldman (1992), and Anselin, Varga, and Acs (1997) provide some evidence for positive externalities generated by university research operating over MSA-scale distances, but the estimated magnitude of these effects is quite sensitive to the level of aggregation over industries and technologies as well as to the definition of the local area. These difficulties in identifying a large, uniform, and real effect of academic research operating at this geographical scale suggest that much closer attention to measurement issues, as well as to the mechanisms and institutions through which these spillovers are transmitted, is needed. Our findings here support this view and prompt further close scrutiny of the phenomenon of the clustering of R&D activities and of the institutional structure of local innovation systems.

Based on the distribution of publications and patents across North American MSAs in three sub-areas of electrical engineering, we find evidence of strong geographic concentration of research. We also find strong evidence for the co-location of downstream industrial R&D with upstream university research at the level of the MSA. While we hesitate to draw any conclusions about a causal relationship between academic research and industrial R&D, the degree of geographical association between these activities suggests a substantial localized component of vertical knowledge spillovers. Interestingly, the magnitude of this effect appears to be strongly mediated by the presence of anchor tenant firms in the local economy. Again, there are obvious and potentially serious endogeneity issues which we have not yet addressed, but the size and persistence of this effect in our regression results suggest an economically significant phenomenon.

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Table I: Matched Pairs: Example from Medical Imaging

MSA	Population	University Papers	Industry Patents	Anchor Tenant
L.A. Riverside Orange County	15608886	55	21	None
New York Northern NJ Long Isl.	19876488	42	43	IBM, Lucent
San Francisco Oakland San Jose	6700753	30	86	Sun, HP
Boston Worcester Lawrence	5827654	28	42	None
Minneapolis St. Paul	2792137	14	15	3M
Atlanta	3627184	11	6	None
Pittsburgh	2361019	7	1	None
Rochester	1086082	6	34	Eastman Kodak

Table II: Matched Pairs: Los Angeles versus New York

	Total Patents	Company MI Patents	Anchor
Los Angeles (21 total MI patents)			
Capistrano Labs Inc.	1	1	
Cardiovascular Imaging Systems Inc.	4	4	
Cordis Webster Inc.	19	1	
Imagyn Medical Technologies Inc.	4	1	
Integrated Medical Systems Inc.	1	1	
International Remote Imaging Systems Inc.	11	5	
Johnson & Johnson Medical Inc.	27	1	
Logicon Inc.	1	1	
Northrop Grumman Corp.	184	1	
Sonus Pharmaceuticals Inc.	1	1	
TOA Medical Electronics Co. Ltd.	2	1	
Vivorx Pharmaceuticals Inc.	16	3	
New York (43 total MI patents)			
Biosense Inc.	6	1	
Center for Laboratory Technology Inc.	1	1	
Ciba Geigy Corp.	178	1	
Cytometrics Inc.	1	1	
Echocath Inc.	5	1	
IBM Corp.	3281	1	X
Lucent Technologies Inc.	1632	1	X
Mobil Oil Corp.	68	1	
Neoromedical Systems Inc.	6	5	
Ortho Diagnostic Systems Inc.	11	1	
Phillips Electronics NA Corp.	257	5	
Sarnoff Corp.	174	5	
Schick Technologies Inc.	1	1	
Siemens Corporate Research Inc.	104	17	
Trex Medical Corp.	5	1	

Table III: Matched Pairs: Minneapolis versus Atlanta

	Total Patents	Company MI Patents	Anchor
Minneapolis (15 total MI patents)			
Clarus Medical Systems Inc.	10	2	
Eastman Kodak Co.	11	1	
Imation Corp.	105	2	
Insight Medical Systems Inc.	1	1	
Medtronic Inc.	470	1	
Micro Medical Devices Inc.	2	1	
Minnesota Mining and Manufacturing Co.	2092	3	X
Picker International Inc.	2	2	
Shturman Cardiology Systems Inc.	15	2	
Atlanta (6 total MI patents)			
General Electric Co.	6	1	
Georgia Tech Research Corp.	129	2	
Minolta-QMS Inc.	1	1	
North American Phillips Corp.	3	2	

Table IV: Descriptive Statistics ($N = 254$)

Variable	Mean	Std Dev	Min	Max
Medical Imaging				
Papers	2.567	7.225	0	55
Patents	2.323	9.567	0	86
Patents (excl. anchors)	2.008	8.947	0	85
No. of anchors (> 1000)	0.031	0.196	0	2
No. of anchors (> 500)	0.039	0.232	0	2
No. of anchors (> 100)	0.122	0.552	0	5
Neural Network				
Papers	2.327	6.581	0	65
Patents	2.287	9.168	0	98
Patents (excl. anchors)	1.831	7.413	0	74
No. of anchors (> 1000)	0.067	0.307	0	2
No. of anchors (> 500)	0.142	0.599	0	6
No. of anchors (> 100)	0.315	1.211	0	13
Signal Processing				
Papers	7.205	19.171	0	154
Patents	18.618	72.941	0	754
Patents (excl. anchors)	15.106	59.354	0	641
No. of anchors (> 1000)	0.079	0.358	0	3
No. of anchors (> 500)	0.169	0.769	0	9
No. of anchors (> 100)	0.602	2.200	0	24
General				
Canadian	0.087	0.282	0	1
Papers (all IEEE)	133.784	324.467	0	2268
Patents (all EE)	387.228	1328.765	0	14227
Papers (all in ISI)	8392.484	19756.09	0	165664
Patents (all in USPTO)	1036.563	2945.978	1	28316
Population	877316.4	1943850	82024	1.99e+07
Income per capita (000's)	22.750	3.986	2.937	38.772
PST labor (000's)	21.332	59.219	0.503	569.807

Table V: Gini Coefficients

	Papers	Patents
Medical Imaging		
Raw locational coeff.	0.443	0.469
Locational coeff. relative to EE	0.440	0.456
Neural Networks		
Raw locational coeff.	0.424	0.458
Locational coeff. relative to EE	0.451	0.454
Signal Processing		
Raw locational coeff.	0.427	0.449
Locational coeff. relative to EE	0.384	0.363
EE locational coeff. relative to total	0.342	0.195

$N = 254$

Table VI: Correlations Between Patents and Papers

Medical Imaging			
	Patents (all)	Patents (excl. anchor)	Papers
Patents (all)	1.000		
Patents (excl. anchor)	0.945	1.000	
Papers	0.581	0.606	1.000
Neural Networks			
	Patents (all)	Patents (excl. anchor)	Papers
Patents (all)	1.000		
Patents (excl. anchor)	0.977	1.000	
Papers	0.520	0.522	1.000
Signal Processing			
	Patents (all)	Patents (excl. anchor)	Papers
Patents (all)	1.000		
Patents (excl. anchor)	0.983	1.000	
Papers	0.761	0.766	1.000

$N = 254$

Table VII: OLS (Co-location)

Dependent Variable: Patents by MSA

	Medical Imaging		Neural Networks		Signal Processing	
Papers	0.769***	0.424***	0.724***	-0.277***	2.894***	1.244***
	(0.068)	(0.110)	(0.075)	(0.089)	(0.156)	(0.261)
PST Labor		0.053***		0.142***		0.635***
		(0.013)		(0.010)		(0.085)
Constant	0.349	0.113	0.603	-0.102	-2.232	-3.878
	(0.520)	(0.509)	(0.522)	(0.392)	(3.181)	(2.889)
$Adj R^2$	0.334	0.370	0.267	0.595	0.577	0.653

*significant at the 0.1 level, ** 0.05, ***0.01.

$N = 254$, standard errors in parentheses.

Table VIII: ZIP (Co-location)

Dependent Variable: Patents by MSA

	Medical Imaging	Neural Networks	Signal Processing
Papers	0.022***	-0.004	0.006***
	(0.004)	(0.003)	(0.000)
$ln(PSTLabor)$	0.386***	0.789***	0.828***
	(0.055)	(0.050)	(0.018)
Constant	0.469**	-0.893***	0.343***
	(0.199)	(0.198)	(0.065)
Zero-Inflation			
No IEEE Papers	1.074**	0.951**	1.370***
	(0.511)	(0.449)	(0.443)
EE Share of Total Patents	-3.929***	-3.357***	-4.467***
	(1.248)	(1.074)	(1.121)
Ln(Population)	-2.003***	-1.125***	-1.245***
	(0.345)	(0.257)	(0.254)
Constant	28.531***	15.984***	15.441***
	(4.849)	(3.599)	(3.315)
Prob > χ^2	0.000	0.000	0.000

*significant at the 0.1 level, ** 0.05, ***0.01.

$N = 254$, Standard errors in parentheses.

$\chi^2(3)$ statistic tests the joint Poisson and Zero-inflation equations against the null of an intercepts-only model.

Table IX: Test of Anchor Tenant Hypothesis using Ordinary and Weighted Least Squares

Dependent Variable: Patents by MSA, Net of Anchor Tenant Patents

	Medical Imaging			Neural Networks			Signal Processing		
	OLS	OLS	WLS[21]	OLS	OLS	WLS	OLS	OLS	WLS
Papers	0.405***	0.424***	0.182***	-0.151*	-0.125*	0.024	1.148***	1.031***	0.449***
	(0.100)	(0.096)	(0.066)	(0.077)	(0.073)	(0.060)	(0.214)	(0.211)	(0.133)
Anchor		-1.393	-2.082		5.154***	5.159***		14.649	6.764
		(3.885)	(2.999)		(1.892)	(1.833)		(13.581)	(11.142)
Anch*Pap		0.750***	0.828***		0.304***	0.353***		1.841**	2.318***
		(0.202)	(0.213)		(0.102)	(0.125)		(0.715)	(0.716)
PST Labor	0.053***	0.024*	0.057***	0.105***	0.070***	0.051***	0.470***	0.334***	0.483***
	(0.012)	(0.013)	(0.012)	(0.009)	(0.010)	(0.011)	(0.069)	(0.077)	(0.067)
Constant	-0.154	0.096	-0.165	-0.057	0.100	0.148	-3.188	-2.058	-1.076
	(0.463)	(0.450)	(0.234)	(0.337)	(0.327)	(0.198)	(2.370)	(2.370)	(1.197)
$AdjR^2$	0.406	0.454	0.390	0.542	0.591	0.408	0.647	0.665	0.584

*significant at the 0.1 level, ** 0.05, ***0.01.

$N = 254$, standard errors in parentheses.

Table X: Test of Anchor Tenant Hypothesis using ZIP

Dependent Variable: Patents by MSA, Net of Anchor Tenant Patents

	Medical Imaging		Neural Networks		Signal Processing	
Papers	0.018***	0.018***	0.001	0.006**	0.007***	0.006***
	(0.004)	(0.005)	(0.004)	(0.003)	(0.000)	(0.001)
Anchor		0.441***		0.953***		0.482***
		(0.103)		(0.119)		(0.043)
$ln(PSTLabor)$	0.604***	0.548***	0.702***	0.446***	0.801***	0.737***
	(0.066)	(0.068)	(0.055)	(0.060)	(0.020)	(0.021)
Constant	-0.614**	-0.464*	-0.812***	-0.215	0.214***	0.349***
	(0.254)	(0.254)	(0.217)	(0.213)	(0.072)	(0.073)
<u>Zero-Inflation</u>						
No IEEE Papers	1.000*	1.015**	0.939**	0.963**	1.378***	1.379***
	(0.529)	(0.528)	(0.454)	(0.447)	(0.454)	(0.449)
EE Share of Total Patents	-4.084***	-4.090***	-3.398***	-3.446***	-4.566***	-4.481***
	(1.365)	(1.363)	(1.093)	(1.084)	(1.158)	(1.133)
Ln(Population)	-1.893***	-1.915***	-1.135***	-1.244***	-1.213***	-1.244***
	(0.357)	(0.357)	(0.258)	(0.255)	(0.257)	(0.255)
Constant	26.975***	27.283***	16.123***	17.640***	15.008***	15.405***
	(5.037)	(5.038)	(3.627)	(3.572)	(3.358)	(3.333)
Prob $> \chi^2$	0.000	0.000	0.000	0.000	0.000	0.000

*significant at the 0.1level, ** 0.05, ***0.01.

$N = 254$, Standard errors in parentheses.

$\chi^2(3)$ statistic tests the joint Poisson and Zero-inflation equations against the null of an intercepts-only model.

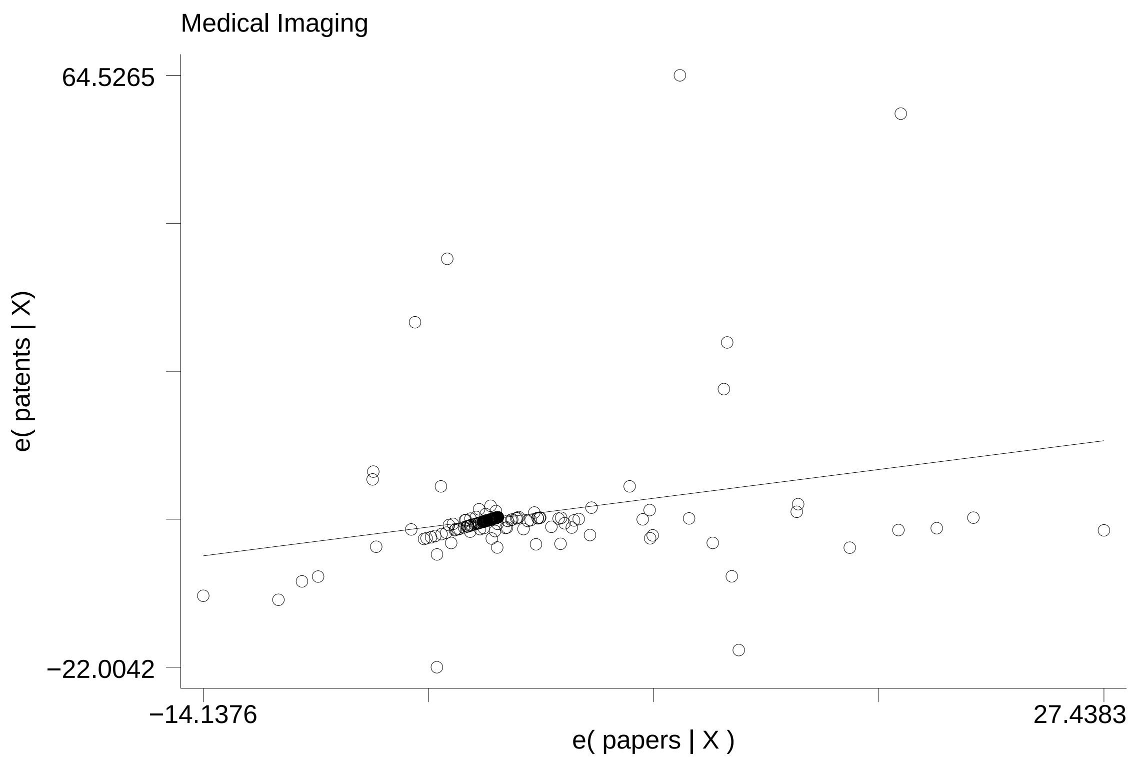

Figure 1: **Medical Imaging**