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ABSTRACT

We examine variation in the concentration of inventive activity across 72 of North America's most highly innovative locations. In 12 of these areas, innovation is particularly concentrated in a single, large firm; we refer to such locations as "company towns." We find that inventors employed by large firms in these locations tend to draw disproportionately from their firm's own prior inventions (as measured by citations to their own prior patents) relative to what would be expected given the underlying distribution of innovative activity across all inventing firms in a particular technology field. Furthermore, we find such inventors are more likely to build upon the same prior inventions year after year. However, smaller firms in company towns do not exhibit this myopic behavior; they draw upon prior inventions as broadly as their small-firm counterparts in more diverse locations. In addition, we find that inventions by large firms in company towns have less impact than those produced elsewhere, although the difference is modest, and that the impact is disproportionately appropriated by the inventing firms themselves. Finally, the geographic scope of impact realized by company town inventions is narrower, whether produced by large or small firms.

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1 Introduction

Firms that choose to locate in cities populated with many other companies incur higher congestion costs. To reconcile this observation economists infer that the agglomeration of economic activity must confer benefits that offset these costs. One such benefit that is central to many theories of agglomeration concerns localized knowledge spillovers. To the extent that firms in economic "hubs" really do enjoy lower cost access to externally generated knowledge one might expect their inventors to be more creative, drawing from a broader pool of ideas in the creation of their inventions. After all, such hubs seem to be unusually fertile locations for entrepreneurial ventures (Acs (2002)), a primary source of so-called creative destruction. Following the same reasoning, one might expect inventors at firms that are located in less economically diverse regions and are thus somewhat isolated from localized knowledge spillovers to be less creative. Furthermore, spatial isolation might influence some firms differently than others. For example, for a variety of reasons we describe below, larger firms in isolated locations might be more susceptible to the Not Invented Here (NIH) Syndrome whereby inventors are more likely to reject externally generated knowledge. We examine these ideas here, exploring how variation in regional economic diversity is related to both the creativity of inventors and the subsequent impact of their inventions.

Interpreting the knowledge production process is central to this line of inquiry. Knowledge externalities – or "spillovers" – play a critical role in most theories of innovation and growth. This reflects the widespread recognition that inventions usually incorporate or build upon ideas or information generated by others and that, in many instances, access to these knowledge production inputs is not explicitly priced. In Alfred Marshall's memorable phrase, ideas are "as it were, in the air."

But are these ideas equally accessible to all potential users? Research on the microfoundations of spillovers suggests not. Knowledge externalities appear to be quite strongly localized (Jaffe et al. (1993),Agrawal et al. (2008)), likely due to their tacitness which makes transfer via face-to-face interactions relatively less costly (Arrow (1962), Polanyi (1966)), hence con-

ferring benefits to co-location and resulting in agglomeration (Rosenthal and Strange (2001), Rosenthal and Strange (2008)). Even in an era of relatively low communication costs and increasingly systematized, codified, and searchable knowledge, inventors appear to be significantly less likely to use knowledge generated in physically distant locations. Furthermore, analysis of the organization and management of corporate R&D has shown that firms invest significant resources in order to develop "absorptive capacity" to enhance their ability to exploit externally generated knowledge (Cohen and Levinthal (1989), Cockburn and Henderson (1998)). In other words, even if not explicitly priced, accessing ideas generated by others is not costless and may be strongly conditioned by institutions, geography, and the optimizing responses of firms and inventors.

However, despite the broad acknowledgement in the literature that localized knowledge spillovers play an important role in agglomeration, there is less consensus around how spillovers are mediated by local economic characteristics. For example, Glaeser et al. (1992) contrast three theories (Marshall-Arrow-Romer, Porter, Jacobs), that emphasize agglomeration benefits due specifically to knowledge spillovers. Yet each of these theories advances a different view on how the importance of spillovers to city growth is influenced by industrial diversity and market structure. The evidence presented in that paper indicates that knowledge spillovers across, rather than within, industries is most important, supporting the idea that diverse regional hubs of economic activity enjoy a productivity advantage relative to other locations. Furthermore, the finding of Feldman and Audretsch (1999) – that regional diversity of economic activity promotes local innovation – provides additional support for Glaeser et al. (1992) and is particularly provocative in that it links the nature of "local knowledge" to theories of "recombinant" growth (Weitzman (1998)).

These ideas are exemplified by the well known success of Silicon Valley – a quintessential hub characterized by technological diversity and many small, entrepreneurial firms (in addition to high-performing large firms) that make up a highly competitive market structure. However, other locations are also innovative but are, relatively, neither technologically diverse

nor particularly dispersed in terms of the local market structure. Route 128 in Massachusetts and Research Triangle Park in North Carolina are locations often contrasted with Northern California since they are dominated by fewer and larger firms. Of course there are much more extreme examples, such as Rochester, New York; Boise, Idaho; and Peoria, Illinois, that, while being innovative locations, are even more concentrated and dominated by a single firm (Kodak, Micron, and Caterpillar, respectively).

How might such variety in city types coexist if the advantages conferred upon firms located in diverse hubs are indeed real and significant? Duranton and Puga (2001) provide a theory of "nursery cities" that integrates the entrepreneurship literature with urban economics by emphasizing the difference in benefits of local market structure and composition across the life cycle of products. Entrepreneurial firms developing new products benefit from being located in diverse cities because they can more easily borrow from different activities but once they have settled on their "ideal process" they benefit from being in specialized cities where production costs are lower.

Other research such as Audretsch and Feldman (1996) and Rosenthal and Strange (2003) has also linked spillovers to location and the composition of production activity, but without an emphasis on diversity. Others have focused on the relationship between knowledge flows and very particular features of regional market structure. For example, Feldman (2003) and Agrawal and Cockburn (2003) link the efficiency of local knowledge spillovers to the presence of large "anchor tenant" firms. Klepper and Simons (2000a) and Klepper and Simons (2000b) also identify the role of industry structure in the sense of incumbents versus entrants driving localized innovation but emphasize knowledge that is internal rather than external to the firm.

Finally, theories focused on factors quite distinct from market structure and technological diversity, such as labor mobility and culture, have been advanced to explain regional variation in knowledge flow patterns. For example, Almeida and Kogut (1999) exploit the variation in intra-regional labor mobility to explain regional differences in the localization of knowledge

spillovers, arguing that the circulation of people within a city drives knowledge flow. On a related theme, in her comparison of Silicon Valley to Route 128, Saxenian (1994) highlights regional variation in the culture of sharing knowledge across organizations (as well as differences in intra-regional mobilitiy) as one of the central explanations for the difference in the performance of firms between those two locations.

In this paper we investigate another factor that might mediate regional knowledge spillover patterns: the NIH Syndrome. Anecdotal evidence suggests that this phenomenon induces R&D workers to discount or ignore sources of knowledge external to their team or organization when insulated from the outside or deprived of diversity in their environment. Katz and Allen (1982) popularized the so-called NIH Syndrome in their study of the propensity of research teams with little turnover to become progressively less productive.[1] The NIH Syndrome has since been widely evoked by practicing managers and in managerially oriented scholarship (Kanter (1983), Leonard-Barton (1995), Chesbrough (2006)), and journalists have identified colorful instances such as Apple Computer in the early 1990s where managers inhabited a "reality distortion field" that led them to reject good ideas because they were not generated in-house.[2] However, there is surprisingly little quantitative evidence as to the prevalence and impact of the NIH Syndrome. A handful of managerial surveys (e.g., de Pay (1989), Mehrwald (1999)) have identified systematic biases against external knowledge, though Menon and Pfeffer (2003) find the opposite effect – a systematic preference for outsider knowledge.

Why might such a bias exist? One reason simply may be that the cost of accessing external knowledge is higher than for accessing internal knowledge. This is likely to be the case when knowledge is transmitted by person-to-person contact or when an organization raises barriers to external sources of knowledge (for example, by restricting participation in peer communities or travel to conferences) in the name of limiting disclosure of trade secrets (Cockburn and Henderson (1998)). Social psychologists also suggest powerful effects of "in-group favoritism"

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[1] Clagett (1967) is an earlier reference.

[2] Burrows, P. "Apple; Yes Steve, You fixed it. Congrats, now what's next?" Business Week, July 31, 2002, p.102.

and "out-group derogation" as mechanisms supporting social identity (Brewer and Brown (1998)). Group affiliation and social identity may be important contributors to self-esteem, satisfaction, or intrinsic motivation (Hogg and Abrams (1988)), and private rewards from affiliating with or strengthening groups may therefore play a significant role in shaping individual behavior. Economists also have interpreted group affiliation and actions that reinforce group membership as efficient mechanisms for supporting coordination or developing trust among group members that facilitate within-group transactions (Glaeser et al. (2000), Efferson et al. (2008)). In addition, it may be the case that these factors that influence the propensity to source knowledge externally are mediated by firm size. Indeed, we will see that large firms seem more susceptible to myopic behavior.

We test for evidence of a systematic bias against the use of knowledge that is external to the firm as shown by the propensity to "self-cite" patents. Our analysis focuses on the role of geography to the extent that location characteristics (i.e., diversity and local market structure) mediate firm-level tendencies towards myopic behavior. We recognize that self-citation may occur for many reasons. Individuals or organizations working in highly specialized fields or on very specific topics are more likely than average to self-cite simply because they constitute a large fraction of the relevant prior work. Self-citation within an organization may also be more likely to occur because of the lower cost of accessing knowledge that is familiar or transmitted by person-to-person contact. We hypothesize that the cultural/behavioral forces driving the NIH Syndrome may be particularly strong in the social or institutional environment where the activity of a single firm dominates the local innovation market. Thus, although the NIH Syndrome may cause elevated levels of self-citation within an organization, laboratory, or work group, it is likely to be difficult to distinguish it from other factors driving self-citation. Here, however, we believe that geography may provide a useful source of identification. If this is the case, then the NIH Syndrome may be visible in the propensity of organizations in such locations to self-cite at a rate that is above baseline.

Specifically, we examine innovation in "company towns" – cities within which innovative

activity is highly concentrated in a few firms, and which also tend to be relatively small in terms of absolute size. In contrast to the positive productivity and growth effects associated with large, diverse, and competitive hubs, in these cities we expect to see a distinct effect of location on innovation. We conjecture that if in fact company town inventors suffer from reduced access to knowledge, then that would be reflected in the prior inventions upon which they choose to build. In other words, creativity in these locations would tend to be more myopic, drawing less upon "outside" knowledge than would be expected given the underlying distribution of knowledge across the economy. This myopia may in turn have a negative impact on the productivity of innovative activity.

We begin our empirical exploration of this issue by examining how myopia in the creative process of invention is related to the concentration of inventive activity across locations. We find that creativity in company towns is indeed more myopic on certain dimensions. In particular, inventors in these locations are more likely than others to build upon prior inventions developed in their own firm, even after controlling for the underlying distribution of relevant innovative activity across all firms. Furthermore, firms in these locations are more likely to draw upon the same set of prior inventions year after year, whether or not it is their own, compared to firms in more diverse locations that more quickly refresh the pool of knowledge upon which they build.

However, perhaps more surprisingly, we find no evidence of this myopic behavior among small firms in company towns. These firms draw just as broadly from external sources in terms of the prior inventions they build upon as their small-firm counterparts in more diverse locations. The NIH Syndrome thus seems to be a feature only of large firms based in company town locations characterized by a lack of technological diversity and a concentrated local market structure of invention.

We then turn to examine whether the observed myopia in company towns matters. Specifically, we examine the relation between creative myopia and the impact on subsequent innovation. We find evidence that innovations from large firms in company towns do in fact have

less impact on subsequent innovation, although the difference is modest, but small firm innovations do not seem to incur a company town discount. In terms of appropriation, a greater fraction of the impact of large firm company town inventions is realized by the inventing firm itself. Finally, the impact of company town inventions, whether from large or small firms, is narrower in geographic scope than those produced in other locations.

Yet, without data to distinguish between impact that is priced (e.g., through licensing) versus non-priced (i.e., a genuine externality of the type specified in Romer (1990)), the implications of our findings for growth are ambiguous. In other words, despite an apparent reduced access to localized knowledge spillovers from other firms, our results offer no basis to conclude that company town innovation is inferior in terms of its contribution to welfare or firm-level productivity relative to that of other locations, even though it appears to be somewhat more myopic at large firms.

2 Data

We construct our sample using data from the United States Patent and Trademark Office (USPTO).[3] We collect all utility patents issued between the years 1985 and 1995, inclusive. This represents 984,888 patents. We limit our focus to the US and Canada and thus drop all patents that do not have at least one inventor residing in either country. This reduces our sample to 540,999 patents. Furthermore, we drop all patents that are not assigned to non-government organizations, including unassigned patents. In other words, we only keep patents assigned to organizations such as firms, universities, and hospitals. This results in a sample of 392,830 patents.

We further refine our sample by focusing only on geographic locations that are reasonably active in innovation. To achieve this, we use city, state/province, and country data associated with inventor addresses to assign each inventor to an MSA. We then count the number of

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[3]Specifically, we use USPTO data that Bronwyn Hall and her collaborators cleaned and coded (Hall et al. (2002)).

patent-inventors per MSA where all inventors are located in the same MSA. For example, if a patent has two inventors, one in Boston and one in New York, we ignore this patent when counting the number of patents in these two cities. However, if both inventors are in Boston, then that patent increases Boston's patent count by one. We then drop the MSAs that have fewer than 500 of these patent-inventors. As such, we focus our attention on the 72 most highly innovative MSAs (down from a total of 408 MSAs). This reduces the total number of focal patents to 264,078. We use this set of patents as our base sample.

3   Methodology

In this section, we describe the empirical techniques employed to address the following two questions: 1) Do inventors based in locations characterized by more concentrated inventive activity exhibit higher levels of creative myopia? 2) Do inventions developed in locations that are more myopic have less impact on future innovation? We use US patent data to construct our key measures of innovative activity and in particular utilize citation data to construct measures of myopia (citations made) and impact (citations received). We begin by defining our two key measures of MSA-level concentration of inventive activity.

3.1   Concentration of Inventive Activity

We measure the concentration of inventive activity across MSAs on two dimensions: 1) across firms and 2) across technology fields. In both cases, we use a Herfindahl-type index to characterize the degree of concentration. We characterize particularly concentrated locations as company towns. We describe the construction of each measure below.

3.1.1   Concentration Across Firms

We base our measure of the concentration of inventive activity on a Herfindahl-type metric that characterizes how patents by inventors in a particular MSA are distributed across firms

(i.e., assignees). In other words, if N_{msa} represents the total number of patents by inventors located in a given MSA and $N_{msa,i}$ represents the number of patents issued to assignee i, then we define our measure $FirmConcentration_{msa}$ as:

$$FirmConcentration_{msa} = \big[1 - \sum_{i \in I} \big(\frac{N_{msa,i}}{N_{msa}}\big)^2\big]\frac{N_{msa}}{N_{msa} - 1}$$

where I is the set of all assignees within the MSA that have been issued a patent.

This measure is similar to the well-known measures of *basicness* and *generality* that Hall et al. (2002) introduced. However, rather than measuring the concentration of citations made and received by a patent in a particular technology field, we instead use it to measure the concentration of firm inventive activity within an MSA. This measure takes values between zero and one, where MSAs with inventive activity more highly concentrated among assignees score values closer to zero and those with greater dispersion obtain values closer to one.[4]

3.1.2 Concentration Across Technology Fields

We construct our technology field concentration measure in a similar fashion. However, rather than measuring the dispersion of patents across assignees, we measure dispersion across two-digit technology fields.[5] Specifically, if $N_{msa,t}$ represents the number of patents developed by inventors located in a particular MSA and categorized as belonging to technology field t, we define our technology field concentration measure $TechnologyConcentration_{msa}$ as:

$$TechnologyConcentration_{msa} = \big[1 - \sum_{t \in T} \big(\frac{N_{msa,t}}{N_{msa}}\big)^2\big]\frac{N_{msa}}{N_{msa} - 1}$$

where T is the set of all technology fields to which patents can be assigned. This measure takes values between zero and one, where MSAs that are more diverse in their technological

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[4]We drop patents that are not assigned when we calculate this measure. However, we test the robustness of our results by treating unassigned patents in an MSA: 1) as if they are all assigned to a single assignee in that location and 2) as if they are each assigned to a different assignee in that location. Our results persist.

[5]Hall et al. (2002) describe the two-digit classification scheme, which has 36 distinct technology categories that can be aggregated into six broad one-digit categories.

landscape obtain values closer to one and those that are more narrowly focused take values closer to zero.[6]

3.1.3   Company Towns

We classify locations that are particularly concentrated along these two dimensions as company towns. Specifically, 12 (16.7%) of our 72 MSAs with the highest levels of innovative activity are measurably more concentrated than the others. We characterize the MSAs with innovation market structure product values ($TechnologyConcentration_{msa} * FirmConcentration_{msa}$) of less than 0.7 as company towns. The value of this product index for each of our company towns is at least 3.5 standard deviations below the mean of the non-company town sample (or 0.84 standard deviations below the mean of the full sample). Perhaps more intuitively, they appear as outliers upon visual inspection of the scatter plot presented in Figure 1.

In descending order according to the overall level of inventive activity as measured by patents, the MSAs we characterize as company towns include: 1) Rochester, NY (Kodak), 2) Albany, NY (General Electric), 3) Saginaw, MI (Dow), 4) Baton Rouge, LA (Ethyl Corp.), 5) Harrisburg, PA (AMP), 6) Ottawa, ON (Nortel), 7)Rockford, IL (Sundstrand Corp.), 8) Boise, ID (Micron Technology Inc.), 9) Binghamton, NY (IBM), 10) Johnson City, TN (Kodak), 11) Melbourne, FL (Harris), and 12) Peoria, IL (Caterpillar).[7]

We list these locations and describe their innovative activity in Table 1. We note several interesting observations about this set of locations. First, they vary considerably in their levels of innovative activity. The largest MSA, Rochester, has just over 10 times the amount of patents (10,950) as the smallest, Peoria (976). Second, in every case the role of the dominant firm is significant. Even in Ottawa, where the dominant firm, Nortel, plays the least significant role relative to the overall inventive activity in its location, it still accounts for more than 30% of all patents invented in that MSA during the sample period. At the other extreme, General Electric accounts for almost 72% of all patents invented in Albany.

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[6]Again, we drop patents that have no specified assignee when we calculate this measure.

[7]We list the dominant firm associated with each company town in brackets.

Third, company towns vary significantly in terms of their importance to the overall inventive activity of their dominant firms. For example, Binghamton and Johnson City account for just under 10% of all inventive activity by IBM and Kodak, respectively. On the other hand, Baton Rouge and Boise account for, respectively, 86% of Ethyl Corp.'s and 97% of Micron Technology Inc.'s overall inventive activities.

Fourth, small firms, which we define simply by their level of inventive activity (less than 400 patents issued over the 11-year study period), account for approximately 20% of inventive activity in Rochester, Albany, and Saginaw, but over 60% in Baton Rouge and Ottawa. It is also interesting to note that while Rochester, Albany, and Saginaw have other large firms in addition to their dominant firm, the other MSAs do not.[8]

Finally, we illustrate the geographic distribution of our company towns in Figure 2. Although we base our data on a sample of patents issued reasonably recently (1985-1995), our company towns are predominantly located in older industrial locations. Specifically, four are in the Northeast (Rochester, Albany, Binghamton, Harrisburg), three are in the Midwest (Peoria, Rockford, Saginaw), three are in the South (Johnson City, Melbourne, Baton Rouge), and only one is in the West (Boise), while one is in Canada (Ottawa).

3.2 Creative Myopia

Creative myopia is a measure of the degree to which inventors are "nearsighted" in drawing disproportionately from prior inventions that are in some way close to them. We employ several myopia metrics to capture different dimensions of distance. These include: 1) Organizational Myopia (building disproportionately on the inventing firm's own prior inventions), 2) Technological Myopia (building disproportionately on prior inventions from the same field as the focal invention), 3) Locational Myopia (building disproportionately on prior inventions from the same MSA as the focal invention), and 4) Historical Myopia (building disproportionately on prior inventions the focal firm has built on before).

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[8] In other words, for most MSAs, the percentage of patents assigned to the dominant firm plus small firms add up to almost 100%.

3.2.1 Organizational Myopia: Self-citation to Own Prior Inventions

We measure this type of myopia by the extent to which a firm's patents draw upon its own prior inventions. We do this by assessing the extent to which citations on a patent refer to prior patents by the same firm as the patent making the citation. Specifically, for each MSA we count the total number of citations, C_{msa}, made by patents produced in the MSA. Of these citations we then count those where the assignee of the citing and cited patents is the same. These are assignee self-citations and their total number is given by C_{msa}^s. Consequently, the average rate at which firms within an MSA make self-citations is given by,

$$\text{SelfCiteMyopia}_{msa} = \frac{C_{msa}^s}{C_{msa}}$$

3.2.2 Technological Myopia

We construct technological myopia in a similar fashion and with the same citation data as organizational myopia. Here, we measure the degree to which firms within an MSA make citations that refer back to patents categorized in the same two-digit technology field as the patents that make the citations. The greater the share of citations that refer to patents in the same technology field, the greater the level of technological myopia. Specifically, if C_{msa} denotes the number of citations made by all patents in a given MSA and C_{msa}^g refers to the number of these citations where the citing and cited patent share the same technology field, then technological myopia is defined as:

$$\text{TechnologyMyopia}_{msa} = \frac{C_{msa}^g}{C_{msa}}$$

3.2.3 Locational Myopia

Locational myopia describes the degree to which patents produced in a given MSA cite prior inventions produced in the same MSA. Although all inventors of each citing patent are located in the same MSA by construction, the inventors associated with cited patents may be

located in multiple MSAs. Consequently, to construct this measure we examine whether the inventor(s) of the citing patent are located in the same MSA as at least one of the inventors of the cited patent. Generally, if the citing patents in an MSA reference a total of C_{msa} patent-MSA pairs and C_{msa}^l of these refer to pairs originating in the same MSA as the citing patents then, the locational myopia measure is given by:

$$\text{LocationMyopia}_{msa} = \frac{C_{msa}^l}{C_{msa}}$$

3.2.4 Historical Myopia: Use of New Knowledge

Considering all patents issued to a firm in a particular year and a particular two-digit technology field, we measure "New Knowledge" as the fraction of the prior art aggregated over this set of patents that is cited by the firm for the first time.[9] Thus, to construct this measure, we determine the number of unique patents, $C_{a,s,t}$, that are cited by assignee a's set of patents issued in year s in technology field t. We further determine the number of these citations made for the first time by assignee a, $C_{a,s,t}^f$. Consequently, we define our new knowledge measure as:

$$\text{NewKnowledgeMyopia}_{a,s,t} = \frac{C_{a,s,t}^f}{C_{a,s,t}}$$

Thus, this measure can take values between zero and one. The closer this measure is to zero, the more myopic the firm's inventive process. That is to say, lower values of this measure indicate that the firm tends to build on the same prior art as it did in the past, even if that prior art was not invented by the firm itself.

At the MSA level, new knowledge myopia is given as the average value of $NewKnowledgeMyopia_{a,s,t}$ across all assignees and technology fields in the MSA during our sample period.

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[9]We are limited to patent data for each assignee back to 1976. Therefore, we drop citations to patents issued before 1976 from both the numerator and denominator of this fractional count measure. Thus, "first time" actually means cited for the first time since 1976. We do not consider this data limitation problematic since our sample includes patents issued between 1985 and 1995.

4   Results

In this section, we report results on our two relationships of interest: 1) concentration of inventive activity and myopic behavior and 2) creative myopia and impact on subsequent innovation. Overall, we find a positive and reasonably strong correlation between concentration and lab-level myopia but only a modest link between myopia and impact.

4.1   Descriptive Statistics

We begin by reporting descriptive statistics in Table 2 and discussing the particularly interesting characteristics of these data. First, the mean level of inventive activity over the 11-year sample period is 3,668 patents (Row 1). It is evident that the distribution is positively skewed by very active locations such as New York, San Francisco, and Boston since the median patent count is only 1,392. These data reveal that on average company towns have significantly less inventive activity than other locations in the sample (1,917 patents compared to 4,018), which, it is useful to recall, is conditioned on locations with high levels of inventive activity. In addition, company towns are, by construction, more concentrated in terms of the distribution of inventive activity across firms and technology fields (Rows 3 and 4).

Since we base all of our myopia measures on citations to prior inventions, it is useful to note that the mean number of citations made by the patents in our sample is approximately 10 (Row 2). In terms of our SelfCiteMyopia variable, on average approximately 9% of the citations the inventors of a patent in our sample make are to prior art from their own firm (Row 5). However, this percentage is significantly higher for the subset of patents that are from company towns (14.4%), foreshadowing the creative myopia of inventors from these locations.

Furthermore, in terms our TechnologyMyopia variable, approximately 64% of the prior art cited by the average patent is in the same technology field as the citing patent (Row 6). Also, on average, Locational Myopia is approximately 30%; that is, about one third of the

prior art cited by the average patent is from the same MSA as the citing patent (Row 7). In addition, on average 91.7% of citations made by a firm in a given year are to prior art the firm has never cited before (Row 8). Finally, in terms of impact, the mean patent in our sample receives a citation from approximately 14 subsequent inventions (Row 10).

We provide insight into the differences in citing behavior between inventors from company towns and those from other locations in Table 3. Although inventors of the average company town patent self-cite with almost twice the propensity of the average patent from other locations (19.5% compared to 10.6%; Column (II), Rows 5 and 6), company town inventors make less than half the proportion of citations to prior art from the local MSA that was not developed by their own firm (2.8% compared to 7.0%; Column (III)). The inventors of the average company town patent also base a smaller fraction of their overall prior art on inventions by other firms that are outside their local MSA (73% compared to 79%; Column (V)).

4.2   Are Company Towns More Myopic?

4.2.1   Matched Patent Results

A comparison of mean values of assignee self-citation rates by company town patents versus those from other locations suggests that a larger fraction of the prior art used in company town inventions is drawn from the inventors' own firm. Specifically, the mean citation rate for company town patents is 14.4%, compared to only 8.7% for other locations (Table 2, Row 5).

However, this simple comparison of means may belie important distributional differences between company town patents and those from other locations. For example, company town firms may be more focused on certain technology fields that lend themselves to higher levels of appropriation (and thus higher self-citations rates). Or company town firms may have had relatively higher levels of innovative activity earlier in our sample period when communication technologies were more costly thus resulting in higher self-citation rates, not because of

creative myopia but rather due to higher costs of accessing external knowledge at the time they were relatively more active.

We employ a matched sample method similar to that pioneered by Jaffe et al. (1993) in order to control for the underlying distribution of innovative activity across technology fields and time.[10] We begin with the set of company town patents where all inventors on each patent, in cases of multiple-inventor patents, are based in the same location. There are 23,007 such patents. We then select a "control patent" for each company town patent using the following algorithm: 1) Construct the control sample from patents originating in the 60 MSAs that are not identified as company towns and that do not have any inventors residing in any of the 12 company town MSAs; 2) Segment this set of patents to ensure matched patents are produced by laboratories of similar size in terms of the number of patents received during the sample period;[11] 3) Of these, identify patents having the same application year as the focal patent; 4) Of these, identify the patent(s) having the most USPC classifications in common with the focal patent. At minimum, eligible control patents will have in common the three-digit technology field. Otherwise, control patents have the same primary classification or the same primary and secondary classification and so on, and we choose the patent that exhibits the greatest degree of similarity with the focal patent. If we are unable to find a control patent with at least the same 3-digit technology field as the focal patent, then we drop the focal patent from the sample; and, 5) If more than one control patent remains as the "best" possible control, then we select the patent closest to the focal patent in terms of issue date as the control (in the event of a tie, we select randomly).[12]

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[10] We fully appreciate the critiques of this method presented in Thompson and Fox-Kean (2005) and Thompson (2006). We address this by matching on both more detailed and multiple technology categories; still, we recognize that the matching process is imperfect. We further address this issue in our conditional logit analysis.

[11] Here patents from large company town laboratories (firms in an MSA that receive 400 or more patents during the sample period) are matched with patents from large labs in more diversified locations. Similarly, patents from small company town laboratories (firms in an MSA that receive less than 400 patents during the sample period) are matched with patents from small labs in more diversified locations.

[12] Given the construction of our matched sample, the potential exists that a given control patent is matched multiple times to different focal patents. In addition, at a broad conceptual level, we note that this methodology implicitly assumes that the spatial distribution of patents, technology, and firms are all exogenous and independent.

We report the average values of our set of myopia measures at the patent level for inventions from company towns versus those from other locations in Table 4. We divide our sample into two, such that patents by large laboratories (with 400 or more patents assigned over the 11-year sample period) are in one subsample and patents assigned to smaller labs are in the other.[13] We base the results presented in the top panel (A) on the large-lab subsample.

The results in the first row indicate that the assignee self-citation rate for company town inventions is 1.27 times higher than for similar patents from more diverse locations; on average 28% of all citations made by company town inventors are to prior inventions from their own firm compared to only 22% in other locations. We interpret this result as suggestive that company town inventors are more myopic in the innovation process than those from other locations.

We also find evidence that company town inventors draw slightly (2%) less widely from other technology fields (Row 2); on average, 66% of citations of company town patents refer to patents in the same technology class as the citing patent while in other locations this is only 63%. This result remains remarkably consistent even when we drop self-citations from the analysis (Row 9). It is important to recall that we conduct our analysis at the two-digit NBER classification level of technological similarity. This is a broad-level taxonomy with category distinctions such as "organic compounds," "drugs," and "biotechnology." So, to the extent that company town inventions draw upon a technologically narrower set of prior ideas within this level of classification relative to other locations we miss detecting differences at that degree of technological specificity.

The results reported in Row 3 indicate that company town inventions from large labs draw 25% more of their prior art from their local area. However, this is primarily the result of their tendency to build upon their own lab's prior art (i.e., same firm, same MSA). When we drop assignee self-citations from the sample (Row 10), we see that these inventors draw

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[13]We use the term "laboratory" to denote the research presence of a firm in a single location. In other words, we would refer to a firm that patents in three locations as having three labs. Where it is obvious that we are referring to a firm in a single location context we use the term "firm" and "lab" interchangeably.

less heavily from other local inventors than inventors in industrially dispersed locations. In other words, company town inventors are not geographically myopic beyond their tendency to build disproportionately on prior art from their own lab. This is underscored when we focus only on lab-level self-citations (Row 4). The large lab self-citation rate of company town inventions is over 40% greater than that of inventions from outside company towns.

The results reported in Row 5 indicate that 79% of the citations made by company town inventors are to prior art that their lab has not cited before. This is less than the 83% of prior art cited by firms in more industrially dispersed locations that is new to the citing firm; moreover, this difference is statistically significant. Furthermore, this result persists when we drop self-citations from the sample (Row 6). In addition, the 4% difference in the fraction of prior art utilized that is new to the inventing firm is more important than it may first appear since this measure is the yearly average. This difference is compounded year after year as firms in more diverse locations refresh the pool of knowledge upon which they build more quickly.

The results reported in Row 7 suggest that large-lab company town inventors build upon slightly newer prior art as measured by citation lag in years.[14] However, this difference is driven by self-citations as this difference disappears when these citations are excluded (Row 11). We find similar results when we examine the citation lag to the most recent citation on a patent, rather than the average lag across all citations (Rows 8 and 12).

In the lower panel (B) of Table 4 we examine the same set of myopia measures, this time applied to the subsample of small labs. Overall, these results indicate that small labs in

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[14]Our temporal myopia measures include the average and minimum citation lags measured in years. Specifically, we define a lag as the difference between the grant year of the citing patent i, ($gyear_i$), and the grant year of a cited patent x, ($gyear_x$). Thus, the average citation lag is the average difference in grant years between the citing patent and each cited patent. That is, if the citing patent makes C citations, then the average citation lag is:

$$\text{AverageCitationLag}_i = \frac{1}{C} \sum_{x=1}^{C} (gyear_i - gyear_x)$$

This is the variable shown on Rows 7, 11, 19 and 23. In contrast, the minimum citation lag is:

$$\text{LagtoMostRecentPatent}_i = min\{gyear_i - gyear_x\}|_{x=1}^{C}$$

This is the variable shown on Rows 8, 12, 20 and 24.

company towns exhibit significantly less myopic behavior than their large-lab counterparts. The differences across our myopia measures between company towns and other locations are much smaller in magnitude and in some cases go in the opposite direction. For example, small-lab inventors are slightly less likely to self-cite than their non-company town counterparts.

To summarize, company town inventors at large labs are myopic in the sense that they are more likely to build upon prior art from their own lab and they are also more likely to build upon prior art their lab has built upon in the past, whether it is their own or invented by others. However, company town inventors at small labs do not exhibit this type of myopic behavior. Also, we find no evidence that company town inventors from large or small labs draw excessively upon older, potentially outdated ideas.

4.2.2 Conditional Logit Results

To confirm the results of the matched pair analysis and to control for other determinants of self-citation, we estimate a conditional logit model for the probability of each citing-cited pair of patents in the sample falling into one of the following mutually exclusive categories: (a) a self-citation within the same "laboratory," (b) a citation made by the focal laboratory to another entity within the same MSA, or (c) a citation to prior inventions developed outside the inventors' own MSA. In the spirit of the classic citation function (Caballero and Jaffe (2002)), we control for differences in the number of potentially citable patents in each category by estimating the McFadden choice model (McFadden (1974)) with the size of the relevant pool of possible citations as an attribute of each of these alternatives.[15] In these regressions, the main variables of interest are the company town dummy and the large laboratory dummy.[16] We also control for MSA size (total number of patents and population), the number of university patents in the MSA, the technology class of the citing patent, and the citation lag (difference between the grant years of the citing and cited patents).

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[15] Citation functions of the type proposed by Caballero and Jaffe (2002) that are estimated from cell counts prove very difficult to estimate for these data since cells are so sparsely populated.

[16] We use the term "large" laboratories to denote those labs that are assigned 400 or more patents over the period under study: 1985-1995.

The results from our conditional logit regression, presented in Tables 5 and 6, suggest a significant degree of myopia in company towns. These tables report the marginal effects at sample means of each explanatory variable on the probability of citations made by a patent falling into each category. All of the estimated marginal effects are significant at the 1% level or better, even with robust standard errors.

In Table 5, the positive and strongly significant effect of the company town dummy on the self-citation and citation-within-MSA outcomes indicates a significant degree of myopia. The magnitude of this effect is substantial. In terms of odds ratios, all else equal, compared to a patent from a less concentrated MSA, a patent generated in a company town is more than three times more likely to self-cite its own lab, relative to the probability of citing a patent originating outside its own location. Citation to the same lab or same MSA is slightly more likely (odds-ratio of 1.04) in larger MSAs (i.e., locations with more overall patents) and less likely in MSAs with more university patents.

The negative coefficient on the citation lag indicates that citations made to older patents are less likely to be a self-citation or a within-MSA citation. There are also significant differences across technology classes and a very large negative effect of the diversity of technology on the probability of self- or within-MSA citation. We obtain very similar results when we add additional controls for the year the citation is made or the year the cited patent is granted.

Table 6 allows for a different effect of being in a company town for small versus large firms. We interact a large-lab dummy (the lab has over 400 patents assigned during the period 1985-1995) with a dummy for company town. The large and positive main effect and interaction effect indicate that myopia is much more significant for larger compared to smaller firms. Estimated coefficients on the other variables are very similar to those in Table 5.

After controlling for a variety of other MSA characteristics, we thus find evidence of significantly higher rates of within-firm and within-MSA citation in company towns. As we find in the matched-pairs analysis, large labs drive this phenomenon. Even after controlling for differences in the size of the pool of self-citable patents, smaller companies are significantly

less likely to cite their own patents or patents originating in the same MSA.

4.3 Does Myopia Hinder Innovation Impact?

The findings we report above suggest that innovation in company towns is more myopic than in other locations. It is tempting to assume that myopia in innovation is undesirable. However, we have no basis upon which to make such an assumption. In this section, we bring this question to the data.

4.3.1 Creative Myopia and the Impact on Future Innovation

We employ the count of citations received by a patent as a proxy for the impact it has had on subsequent innovation. Several studies have shown the number of citations received to be correlated with various measures of patent value, including patent renewals (Harhoff et al. (1999)), consumer surplus (Trajtenberg (1990)), expert opinion (Albert et al. (1991)), and market value of the assignee firm (Hall et al. (2005)).[17]

We compare the relative impact of inventions across location types using the matched sample method. To this end we employ the same sample of matched patents as that described above to determine whether patents originating in company towns receive fewer citations than similar patents originating in more industrially diverse locations.

In Table 7 we report the average number of citations received by inventions from company towns versus those from other locations. Using the same matched sample as described above, we present results based on patents by large labs in the top panel and by small labs in the lower panel.

We report the main result in the first row of the table. Patents by inventors at large firms in company towns have less impact on subsequent innovation than other patents in the

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[17]In addition, the interpretation of citations received as a proxy for impact is consistent with that held by the USPTO: "If a single document is cited in numerous patents, the technology revealed in that document is apparently involved in many developmental efforts. Thus, the number of times a patent document is cited may be a measure of its technological significance." (Office of Technology Assessment and Forecast, Sixth Report, 1976, p. 167).

same technology field, although the difference is modest (8%) . However, this is not true for the impact of small firms. In this case, patents from company towns receive just as many citations as those from more diverse locations (Row 10).

Consistent with our prior results based on citations made, patents by inventors at large company town firms receive 1.8 times the number of self-citations received by similar patents from more diverse locations. In other words, given the slightly smaller overall impact of patents from large firms in company towns, a much larger fraction of the impact is realized by the (large) inventing firm itself in company towns compared to elsewhere (Row 2). This is not the case with small firms (Row 11).

We find no evidence that the impact of company town patents is more technologically concentrated than patents in more diverse locations. Between 40 and 50% of all citations received come from outside the focal patent's own technology field. This applies to both large and small firms (Rows 3 and 12).

Consistent with other findings in prior studies concerning the localization of knowledge flows, such as Jaffe et al. (1993), Thompson and Fox-Kean (2005), Agrawal et al. (2006), and Rosenthal and Strange (2008), we find that firms receive a significant fraction of their citations from patents produced in their own MSA (Row 4). However, the greater tendency of large company town firms to receive citations from their own MSA is attributed to the fact that they internalize more of the benefits of their own research relative to firms in other locations. The results reported in Row 8, where we drop assignee self-citations, confirm this intuition; comparing the number of citations received from local inventors, patents in industrially dispersed locations receive more than twice the number of citations as those received by company town inventions.

In terms of the geographic scope of their impact, patents produced in company towns seem to have less impact regardless of the size of the producing lab. Large lab inventions developed in company towns are cited in only 4.55 unique MSAs on average compared to inventions developed in other locations that are cited in 5.11 unique MSAs (Row 6). In other words,

inventions from company towns impact subsequent innovation in 10% fewer locations, on average. Upon excluding self-citations the difference becomes even more dramatic. Company town inventions impact subsequent innovation in approximately 17% fewer locations (Row 9). The company town effect on smaller labs is present, but less pronounced. The company town discount is approximately 3% and increases to 4% when self-citations are excluded (Rows 15 and 18).

5 Conclusion

Company towns are an interesting feature of the geography of innovation: Inventive activity in some locations is dominated by a single organization, which may have important implications for the economics of localized knowledge spillovers. We find that in these locations, large firms tend to be more myopic than those in locations where the inventive activity is less concentrated. However, smaller firms located in company towns do not exhibit myopic behavior, suggesting that geography need not dictate access to knowledge produced elsewhere. Instead, geographic isolation may facilitate the development of certain attitudes towards innovation to which inventors in large-firm environments might be particularly susceptible.

The causes of this myopia are unclear. One hypothesis is that it reflects the Not Invented Here Syndrome, the alleged tendency of R&D workers to discount or ignore knowledge from sources external to their organization or work team. In large firms located in company towns, this propensity may be particularly strong.

The NIH Syndrome is generally thought to have a negative impact on the productivity of R&D; if this is true, then the myopia we observe should have a negative effect on the impact of these inventions. Interestingly, however, we see only modest evidence of this, at least as captured by the number of citations received by the patents belonging to the large firms in our sample. Myopic inventors in large firms tend to produce patents that are less likely to be cited externally, but this is largely made up for by higher levels of internal citations. Furthermore, it may be that the economic value of patents that are disproportionately self-cited is lower. In

this case, myopia would have an even greater negative impact. But this finding also points to potential benefits associated with "in group favoritism" as a mechanism supporting efficient internal exchange and coordination.

The forward citation patterns we observe, both higher rates of self-citation and a narrower scope of geographic impact, are also consistent with firms in company towns having a higher ability to appropriate returns from R&D. Choosing to be geographically isolated may be an effective way to limit spillovers to competitors. In other words, geographic isolation may lower the cost of appropriating knowledge developed in-house while at the same time increase the cost of accessing externally generated knowledge. The fact that some firms choose to locate in company towns while others do not reveals differences in the relative costs and benefits associated with knowledge appropriation and access across firms. As noted above, our empirical analysis implicitly assumes that the spatial distribution of firms and technology is exogenous and independent. If instead we allow for endogenous optimizing choices of location the interpretation of these results may be rather different. Identifying firm characteristics that underlie differences in the relative costs and benefits associated with knowledge appropriation and access is the next logical step in this line of inquiry.

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Table 1: Company Towns

MSA	Dominant Firm	Dominant Technology	Total Patents in MSA	No. of Patents Assigned to Dominant Firm in MSA	% of MSA's Patents Assigned to Dominant Firm	Number of Patents Assigned to Dominant Firm Worldwide	% of Dominant Firm's Total Patents in this MSA	% of MSA's Patents Assigned to Small Firms[1]
Rochester (NY)	Kodak	chemicals	10,950	5,304	48.4	6,793	78.1	20.2
Albany (NY)	GE	electronics	5,255	3,773	71.8	9,073	41.6	20.6
Saginaw (MI)	Dow	chemicals	3,441	1,740	50.6	3,916	44.4	22.5
Baton Rouge (LA)	Ethyl Corp.	chemicals	2,010	718	35.7	836	85.9	64.3
Harrisburg (PA)	AMP	electronics	1,835	1,096	59.7	1,784	61.4	40.3
Ottawa (ON)	Nortel	computers	1,637	498	30.4	966	51.6	69.6
Rockford (IL)	Sundstrand	electronics	1,599	756	47.3	1,063	71.1	52.7
Boise (ID)	Micron	electronics	1,344	558	41.5	576	96.9	58.5
Binghamton (NY)	IBM	computers	1,266	814	66.4	8,850	9.2	33.6
Johnson City (TN)	Kodak	chemicals	1,118	627	56.1	6,793	9.2	43.9
Melbourne (FL)	Harris	electronics	1,080	467	43.2	706	66.1	56.8
Peoria (IL)	Caterpillar	mechanical	976	639	65.5	820	77.9	34.5

We base the sample on US patents issued to non-government organizations between 1985-1995, inclusive, where at least one inventor is located in the US or Canada. [1]Small firms receive less than 400 patents during the sample period.

Table 2: Descriptive Statistics

	All MSAs Mean	All MSAs Median	Company Towns Mean	Other Locations Mean
1. Patent count by MSA	3,668 (5,470)	1,392	1,917 (2,421)	4,018 (5,845)
2. No. Citations Made by Patent	9.665 (1.583)	9.638	8.568 (1.499)	9.885 (1.517)
Concentration[1]				
3. Firm	0.871 (0.163)	0.935	0.550 (0.149)	0.935 (0.053)
4. Technology	0.916 (0.050)	0.931	0.841 (0.086)	0.931 (0.014)
Myopia[2]				
5. Assignee (Self-Citation)	0.097 (0.047)	0.091	0.144 (0.073)	0.087 (0.034)
6. Technology	0.641 (0.034)	0.639	0.652 (0.057)	0.638 (0.028)
7. Location	0.301 (0.117)	0.290	0.377 (0.182)	0.286 (0.094)
Percentage of New Citations[3]				
8. All Citations	0.917 (0.020)	0.912	0.915 (0.032)	0.917 (0.017)
9. Excluding Self-Citations	0.919 (0.019)	0.914	0.923 (0.029)	0.918 (0.016)
10. No. Cites Rcvd by Patent	14.422 (4.591)	13.586	14.843 (8.098)	14.337 (3.619)
11. No. of Patents[4]	264,078		23,007	241,071

Standard deviations in parenthesis. [1]*Concentration* measures the dispersion of patents within an MSA across firms (or 2-digit technology classifications) using a Herfindahl type measure where lower values reflect higher levels of concentration; here, "Firm" is equivalent to Assignee. [2]*Myopia* measures the rate at which a citing and cited patent have the same specified characteristic (i.e., same assignee, 2-digit technology classification, or MSA). [3]*Percentage of New Citations* is the MSA average annual percentage of cited patents that are cited for the first time; here, "Self-Citations" are citations between citing and cited patents with the same assignee. [4]This is the total number of patents aggregated over all MSAs in the sample; company towns versus all other MSAs are broken out in the latter two columns.

Table 3: Decomposition of Prior Art

	Citations Made (I)	MSA Self-Cites Assignee Self-Cites[1] (II)	MSA Self-Cites Assignee Non-Self-Cites[2] (III)	MSA Non-Self-Cites Assignee Self-Cites[3] (IV)	MSA Non-Self-Cites Assignee Non-Self-Cites[4] (V)
Absolute Number					
1. All Patents	6.891	0.684	0.441	0.267	5.498
2. Company Towns	6.815	1.246	0.204	0.351	5.014
3. Other Locations	6.899	0.631	0.464	0.259	5.545
Share of Citations					
4. All Patents	7.323	0.114	0.066	0.036	0.785
5. Company Towns	7.138	0.195	0.028	0.046	0.731
6. Other Locations	7.340	0.106	0.070	0.035	0.790

Elements in Columns (II) to (V) may not add up to elements in Column (I) due to rounding. [1]Count of citations per patent where the citing and cited patents are both produced in the same MSA and have the same assignee; [2]Count of citations per patent where the citing and cited patents are both produced in the same MSA but have different assignees; [3]Count of citations per patent where the citing and cited patents are produced in different MSAs but have the same assignee; and, [4]Count of citations per patent where the citing and cited patents are produced in different MSAs and have different assignees.

Table 4: Creative Myopia: Company Towns versus Other Locations

| | No. of Matched Pairs | Patent Mean by: | | Difference in Means | t-statistic |
| | | Company Towns | Other Locations | | |
	(I)	(II)	(III)	(II) - (III)	
A. Large Lab[1]					
Self-Citation Rate[2]					
1. Assignee	14,992	0.28	0.22	0.06***	17.82
2. Technology	14,992	0.66	0.63	0.02***	6.14
3. MSA	14,992	0.25	0.20	0.06***	18.26
4. Lab	14,992	0.23	0.16	0.07***	22.56
Percentage of New Citations[3]					
5. All Citations	15,851	0.79	0.83	-0.04***	-25.55
6. Excluding Self-Citations	15,851	0.83	0.86	-0.03***	-18.26
Citation Lag (Years)[4]					
7. Average All Patent Citations	14,992	6.15	6.40	-0.25**	-2.05
8. To Most Recent Cited Patent	14,992	2.83	3.00	-0.18***	-4.09
Excluding Assignee Self-Citations					
Self-Citation Rate[2]					
9. Technology	13,173	0.65	0.63	0.01***	3.39
10. MSA	13,173	0.03	0.04	-0.01***	-6.12
Citation Lag (Years)[4]					
11. Average All Patent Citations	13,173	6.49	6.55	-0.06	-1.10
12. To Most Recent Cited Patent	13,173	3.51	3.55	-0.05	-1.32
B. Small Lab[5]					
Self-Citation Rate[2]					
13. Assignee	5,099	0.12	0.12	0.001	0.11
14. Technology	5,099	0.69	0.67	0.01**	2.12
15. MSA	5,099	0.13	0.14	-0.01**	-2.15
16. Lab	5,099	0.09	0.07	0.01***	3.14
Percentage of New Citations[3]					
17. All Citations	4,318	0.91	0.89	0.02***	5.16
18. Excluding Self-Citations	4,318	0.92	0.89	0.02***	5.74
Citation Lag (Years)[4]					
19. Average All Patent Citations	5,099	6.37	6.37	0.001	0.02
20. To Most Recent Cited Patent	5,099	3.22	3.10	0.12**	2.33
Excluding Assignee Self-Citations					
Self-Citation Rate[2]					
21. Technology	4,810	0.68	0.67	0.01**	2.06
22. MSA	4,810	0.05	0.08	-0.03***	-7.78
Citation Lag (Years)[4]					
23. Average All Patent Citations	4,810	6.54	6.57	-0.03	-0.42
24. To Most Recent Cited Patent	4,810	3.57	3.42	0.15***	2.65

*** = significant at 1%, ** = significant at 5%. [1]A Large Lab is an assignee in a particular MSA that obtains 400 or more patents during the sample period. [2]*Self-Citation Rate* measures, at the patent level, the rate at which a citing and cited patent have the same assignee (or 2-digit technology classification, or MSA, or Lab). [3]*Percentage of New Citations* is the MSA average annual percentage of cited patents that are cited for the first time. [4]*Citation Lag* measures, at the level of the citing patent, the time lag between citing and cited patent issue years. [5]A Small Lab is an assignee in a particular MSA that obtains *less* than 400 patents during the sample period.

Table 5: Conditional Logit Regression: Marginal Effects

	Lab Level Self-Citation[1]	Citation within MSA (non-self-cite)[2]	Citation Outside MSA[3]
Citing-cited pair specific variables			
Citing Patent MSA:			
Company Town Dummy	0.028*	0.042*	-0.070*
	33.41	30.17	-45.59
No. of Patents in MSA	0.0004*	0.005*	-0.006*
	21.26	70.83	-74.67
Number of University Patents in MSA (1000s)	-0.002*	-0.033*	0.035*
	-4.55	-28.50	28.87
MSA Population (millions)	-0.0002*	-0.005*	0.005*
	-6.48	-37.61	38.41
MSA Technology Dispersion	-0.033*	-0.044*	0.077*
	-9.89	-4.10	6.91
Citing-cited Patent Citation Lag	-0.001*	-0.009*	0.010*
	-52.05	-116.06	128.12
Citing Patent Technology Class Effects	x	x	x
Choice Specific Variables			
Number of Citable Patents in MSA	1.4E-10*	-9.00E-09*	8.90E-09*
	8.92	-8.92	8.92
Number of Citable Patents Outside MSA	8.3E-10*	8.90E-09*	-9.70E-09*
	8.92	8.92	-8.92
Number of Potential Self-cites	-9.70E-10*	1.40E-10*	8.30E-10*
	-8.92	8.92	8.92

Robust standard errors. * = significant at 1%. N = 4,923,693. The dependent variable identifies a citation: [1]within the same "laboratory" (where citing and cited patents are produced in the same MSA and issued to the same assignee); [2]made by the focal laboratory to another entity within the same MSA (where citing and cited patents are produced in the same MSA but are issued to different assignees); and, [3]to prior inventions developed outside the inventors' own MSA (where citing and cited patents are produced in different MSAs).

Table 6: Conditional Logit Regression: Marginal Effects, Disaggregated by Lab Size

	Lab Level Self-Citation[1]	Citation within MSA (non-self-cite)[2]	Citation Outside MSA[3]
Citing-cited pair specific variables			
Citing Patent MSA:			
Company Town Dummy	-0.003*	-0.013*	0.015*
	-4.25	-5.74	6.77
Large Lab Size Dummy	0.003*	0.050*	-0.053*
	12.79	66.50	-68.04
Company Town Dummy X Large Lab Size Dummy	0.038*	0.034*	-0.072*
	14.87	11.95	-20.82
No. of Patents in MSA	0.0003*	0.005*	-0.005*
	17.13	62.95	-65.89
Number of University Patents in MSA (1000s)	-0.001*	-0.025*	0.025*
	-1.69	-21.71	21.41
MSA Population (millions)	-0.0001*	-0.004*	0.004*
	-3.33	-31.79	31.91
MSA Technology Dispersion	-0.049*	-0.093*	0.141*
	-15.02	-8.49	12.34
Citing-cited Patent Citation Lag	-0.001*	-0.009*	0.010*
	-51.40	-114.29	126.13
Citing Patent Technology Class Effects	x	x	x
Choice specific variables			
Number of Citable Patents in MSA	1.70E-10*	-1.10E-08*	1.10E-08*
	10.62	-10.62	10.62
Number of Citable Patents Outside MSA	9.80E-10*	1.10E-08*	-1.20E-08*
	10.62	10.62	-10.62
Number of Potential Self-cites	-1.10E-09*	1.70E-10*	9.80E-10*
	-10.62	10.62	10.62

Robust standard errors. * = significant at 1%. N = 4,923,693. The dependent variable identifies a citation: [1]within the same "laboratory" (where citing and cited patents are produced in the same MSA and issued to the same assignee); [2]made by the focal laboratory to another entity within the same MSA (where citing and cited patents are produced in the same MSA but are issued to different assignees); and, [3]to prior inventions developed outside the inventors' own MSA (where citing and cited patents are produced in different MSAs).

Table 7: Impact Measured by Citations Received[1]

	No. of Matched Pairs	Patent Mean by:		Difference in Means	t-statistic
		Company Towns	Other Locations		
	(I)	(II)	(III)	(II) - (III)	
A. Large Lab Patents Matched					
Includes Assignee Self-Citations					
1. All Citations	16,266	13.24	14.30	-1.07***	-5.08
2. Citations Received from same Assignee	16,266	3.73	2.04	1.69***	21.51
3. Citations Received from same Technology	16,266	7.70	7.51	0.19	1.46
4. Citations Received from Focal MSA	16,266	3.86	2.87	0.99***	11.61
5. Citations Received from Same Lab	16,266	3.29	1.63	1.66***	23.14
6. Number of Unique Citing MSAs[2]	16,266	4.55	5.11	-0.55***	-12.91
Excludes Assignee Self-Citations					
7. Citations Received from same Technology	16,266	5.40	6.39	-0.99***	-9.43
8. Citations Received from Focal MSA	16,266	0.56	1.24	-0.68***	-19.36
9. Number of Unique Citing MSAs[2]	16,266	3.81	4.59	-0.77***	-18.98
B. Small Lab Patents Matched					
Includes Assignee Self-Citations					
10. All Citations	5,757	12.96	13.11	-0.15	-0.44
11. Self-Citations Received from same Assignee	5,757	0.95	1.17	-0.22***	-2.85
12. Citations Received from same Technology	5,757	8.03	7.89	0.14	0.60
13. Citations Received from Focal MSA	5,757	2.01	2.16	-0.15	-1.08
14. Citations Received from Same Lab	5,757	0.68	0.86	-0.18***	-2.81
15. Number of Unique Citing MSAs[2]	5,757	5.33	5.52	-0.19**	-2.46
Excludes Assignee Self-Citations					
16. Citations Received from same Technology	5,757	7.37	7.12	0.25	1.13
17. Citations Received from Focal MSA	5,757	1.33	1.30	0.03	0.29
18. Number of Unique Citing MSAs[2]	5,757	5.02	5.22	-0.20***	-2.66

*** = significant at 1%, ** = significant at 5 %. [1]*Citations Received* measures, at the patent level, the number of citations a focal patent receives from patents exhibiting the specified characteristic (e.g. same assignee, 2-digit technology classification, etc.).
[2]Measures the number of distinct MSAs that produce patents that cite the focal patent.
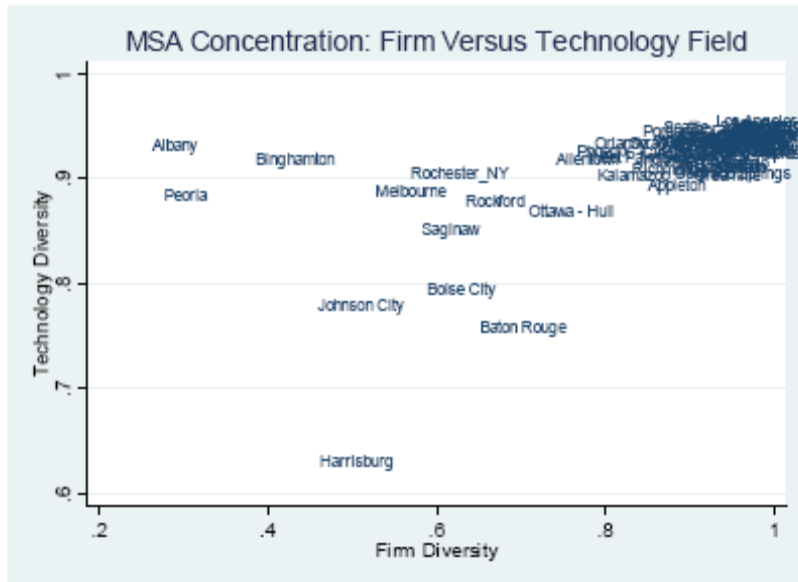
Figure 1 – Concentration of Inventive Activity

MSA Concentration: Firm Versus Technology Field

Figure 2 – Map of Company Towns