Not Invented Here:

Creative Myopia and Company Towns

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Abstract

We examine variation in the market structure of innovation across 72 of North America's most highly innovative locations. In 12 of these areas, innovative activity is particularly concentrated in a single large firm; we refer to such locations as "company towns." We find that inventors in these locations tend to draw disproportionately from their firm's own prior art relative to what would be expected given the underlying distribution of innovative activity across all inventing firms. Furthermore, we find that inventors in company towns are more likely to draw upon the same prior art year after year as opposed to those in more industrially diverse locations. We refer to this tendency as "creative myopia." However, even though a greater fraction of the impact from company town inventions is realized by the inventing firm itself, we find no evidence that inventions from this type of location have any less impact on subsequent innovation overall, nor do we find that the geographic scope of their influence is in any way diminished.

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1 Introduction

Scholars of innovation and economic geography have focused much attention on locations such as California's Silicon Valley, Massachusetts' Route 128, and North Carolina's Research Triangle, which have attracted clusters of firms that seemingly benefit from agglomeration economies due to factors such as thicker labor markets, knowledge spillovers, and indivisibilities resulting from economies of scale in research and development. However, much less attention has been paid to innovative locations dominated by a single, large, research-intensive firm. This is surprising since such locations also play an important role in North America's innovation landscape. These regions include the Rochester metropolitan statistical area (MSA), which is dominated by Kodak (chemicals and optics); the Albany MSA, which is dominated by General Electric (electronics and chemicals); and the Binghamton MSA, which is dominated by IBM (computer hardware and software), among others. We classify such locations as "company towns."

To the extent that knowledge spillovers between firms are important (not just from a macroeconomic endogenous growth perspective but also in terms of firm-level, innovation-related productivity) and recognizing that the single most well-documented empirical observation about spillovers is that they are geographically localized, one might infer that inventors in such isolated, non-clustered locations are disadvantaged. We conjecture that if in fact company town inventors suffer from reduced access to knowledge spillovers, then that would be reflected in the prior art 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.

We explore this issue by examining how myopia in the creative process of invention is related to the market structure of innovative activity across locations. Perhaps surprisingly, 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 art 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 prior art 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 most surprisingly, we find no evidence of company town myopia in several other key dimensions. Inventors in company towns are not more likely than others to draw upon prior art in the same technology field that they are working in. Nor are they more likely to draw upon prior art from their own MSA (after controlling for that from their own firm). Moreover, these inventors are also no more likely than others to draw upon prior art that is less current (i.e., older). In other words, company town inventors do not appear to be as isolated from national and international knowledge flows as their geography might suggest.

Having concluded that company town inventors seem to be myopic in terms of some dimensions of the creative process but not others, we then turn to examining whether the observed myopia matters. Specifically, we examine the relation between creative myopia and impact on subsequent innovation. We find no evidence that company town inventions have less impact on future innovation. Furthermore, although a larger fraction of the impact from company town inventions is realized by the inventing firm itself, the impact of these inventions is no less geographically dispersed.

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 welfare implications of differences in the degree of appropriation, captured here by the propensity to self-cite, are not obvious, especially since the overall level of impact is similar across locations. Thus, despite an apparent reduced access to localized knowledge spillovers from other firms, our preliminary findings 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.

2 Background

Knowledge externalities – or "spillovers" – play a critical role in most theories of innovation and growth, reflecting the widespread recognition that inventions usually incorporate or build upon ideas or information generated by others and that in many instances access to these inputs to the knowledge production function 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. On the one hand, knowledge externalities appear to be quite strongly localized (Jaffe et al. (1993), Rosenthal and Strange (2001), Rosenthal and Strange (2008), Agrawal et al. (2008)). Even in an era of relatively low communications costs and increasingly systematized, codified, and searchable knowledge, inventors appear to be significantly less likely to use knowledge generated in physically distant locations. On the other hand, 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.

One interesting and important factor driving the cost of accessing knowledge spillovers is the structure of local innovation markets. The foundational work of Glaeser et al. (1992), Audretsch and Feldman (1996), and Rosenthal and Strange (2003), among others, has linked knowledge spillovers to the location and composition of production activity. The finding of Feldman and Audretsch (1999) – that diversity of economic activity at a given location promotes innovation – is particularly provocative in that it links the nature of "local knowledge" to theories of "recombinant" growth (Weitzman (1998)). Other research has linked spillovers to industry structure in the industrial organization sense; for example, Feldman (2003) and Agrawal and Cockburn (2003) link the efficiency of local knowledge spillovers to the presence of large "anchor tenant" firms.[1]

Here we investigate another potential source of heterogeneity in the cost of accessing spillovers: the (alleged) propensity of R&D workers to discount or ignore sources of knowledge that are external to their team or organization. Katz and Allen (1982) popularized the so-called "Not Invented Here (NIH) Syndrome" in their study of the propensity of research teams with little turnover to become progressively less productive.[2] 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.[3] But 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) and Mehrwald (1999)) have identified systematic biases against external knowledge, though Menon and Pfeffer (2003) found the opposite effect – a systematic preference for outsider knowledge.

Why might such a bias exist? One reason may simply 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" and "out-group derogation" as mechanisms supporting social identity (Brewer and Brown (1998)). Group affiliation and social identity may be an important contributor to self-esteem, satisfaction, or intrinsic motivation (Hogg and Abrams (1988)), and private rewards from affiliating with groups, or strengthening groups, may therefore play

[1] 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.

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

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

a significant role in shaping individual behavior. Economists have also interpreted group affiliation and actions that reinforce group membership as efficient mechanisms for supporting co-ordination among group members or developing trust between group members that facilitates within-group transactions (Glaeser et al. (2000), Efferson et al. (2008)).

In this paper, we test for evidence of a systematic bias against 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, in the sense that the "Here" in our analysis of Not Invented Here refers to a location as much as to an organization. We recognize that self-citation may occur for many reasons. An individual or organization that works in a highly specialized field or a very specific topic is 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 Not Invented Here Syndrome may be particularly strong in the social or institutional environment of company towns 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."

3 Data

We construct our sample using data from the United States Patent and Trademark Office (USPTO).[4] We collect all utility patents issued between the years 1985 and 1995, inclusive.

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

This represents 984,888 patents. We limit our focus to North America and thus drop all patents that do not have at least one inventor residing in the US or Canada. This reduces our sample to 543,806 patents. Furthermore, we drop all patents that are not assigned to non-government organizations, including unassigned patents. In other words, we only keep patents that are assigned to organizations such as firms, universities, and hospitals. This results in a sample of 424,174 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 patent-inventors per MSA. For example, if a patent has two inventors, one in Boston and one in New York, that patent increases the counter for each of those MSAs by one. However, if both inventors are in Boston, then that patent only increases the Boston MSA counter by one. We then drop the MSAs that have fewer than 500 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 342,508. We use this set of patents as our base sample.

4 Methodology

We set out to address two empirical questions: 1) Do inventors that are based in locations characterized by a more concentrated market structure of innovation exhibit higher levels of creative myopia? 2) Do inventions that are developed in locations that are more myopic have less impact on future innovation?

In this section, we describe the empirical techniques employed to address these questions. 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 market structure.

4.1 Market Structure of Innovation

We measure the market structure of innovative activity across MSAs on two dimensions: 1) innovative activity across firms and 2) innovative activity across technology fields. In both cases, we use a Herfindahl-type index to characterize the market structure. Furthermore, we use these measures as a way of identifying highly concentrated locations, which we categorize as company towns. We describe each measure below.

4.1.1 Market Structure of Innovative Activity Across Firms

Our measure of the market structure of innovation is based 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* introduced by Hall et al. (2002). However, rather than measuring 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 a greater concentration of assignee activity score values closer to zero and those with greater dispersion obtain values closer to one.[5]

[5] 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 were all assigned to a single assignee in that location and 2) as if they were each assigned to a different assignee in that location. Our main results persist.

4.1.2 Market Structure of Innovative Activity Across Technology Fields

We construct our technology field market structure measure in a similar fashion. However, rather than measuring the dispersion of patents across assignees, we measure dispersion across two-digit technology fields.[6] 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 market structure measure, $TechnologyConcentration_{msa}$, as:

$$TechnologyConcentration_{msa} = \left[1 - \sum_{i \in I} \left(\frac{N_{msa,t}}{N_{msa}}\right)^2\right] \frac{N_{msa}}{N_{msa} - 1}$$

This measure takes values between zero and one, where MSAs that are more diverse in their technological landscape obtain values closer to one and those that are more narrowly focused take values closer to zero.[7]

4.1.3 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 market structure product values ($TechnologyConcentration_{msa} * FirmConcentration_{msa}$) of less than 0.6 as company towns. Perhaps more intuitively, they appear as outliers upon visual inspection of the scatter plot presented in Figure 1.

The MSAs we characterize as company towns include, in descending order according to the overall level of innovative activity as measured by patents: 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 City, ID (Micron Technology Inc.), 9) Binghamton, NY (IBM), 10) Johnson City, TN

[6] The two-digit classification scheme, which has 36 distinct technology categories that can be aggregated into six broad one-digit categories, is described in Hall et al. (2002).

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

(Kodak), 11) Melbourne, FL (Harris), and 12) Peoria, IL (Catepillar).

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 (10,952) 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 innovative activity in its location, it still accounts for over 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. Third, company towns vary significantly in terms of their importance to the overall innovative activity of their dominant firms. For example, Binghamton and Johnson City account for just under 10% of all innovative activity by IBM and Kodak, respectively. On the other hand, Baton Rouge and Boise City account for, respectively, 86% of Ethyl Corp.'s and 97% of Micron Technology Inc.'s overall innovative activities.

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 City), while one is in Canada (Ottawa).

4.2 Creative Myopia

Creative myopia is a measure of the degree to which inventors are "nearsighted" in drawing disproportionately from prior art that is in some way close to them. We employ several myopia metrics to capture different dimensions of distance. These include: 1) Firm-level myopia: Self-cite (building disproportionately on the inventing firm's own prior art), 2) Firm-level myopia: New Knowledge (building disproportionately on prior art the focal firm has built on before), 3) Technology-level myopia (building disproportionately on prior art from the same field as the focal invention), 4) Location-level myopia (building disproportionately on prior art invented in the same MSA as the focal invention), and 5) Temporal myopia (building disproportionately on older prior art). We describe the construction of each of these measures in turn.

4.2.1 Firm-level Myopia: Self-cite

This type of firm-level myopia is captured by the extent to which a firm's patents draw upon its own prior art. For each inventing firm, we construct the set of all prior art it cites in a given year (aggregated over all the patents issued to that firm that year). We then calculate the fraction of the prior art cited that belongs to the focal firm (i.e., the fraction of cites that are self-cites). Specifically, if $C_{a,s}$ is the number of patents cited by assignee a in year s and $C^a_{a,s}$ is the number of citations that refer to a's prior patents, then this firm level myopia measure is given by,

$$\text{SelfCiteMyopia}_{a,s} = \frac{C^a_{a,s}}{C_{a,s}}$$

4.2.2 Firm-level Myopia: New Knowledge

Considering all patents issued to a firm in a particular year and a particular two-digit technology field, "New Knowledge" measures the fraction of the prior art aggregated over this set of patents that is cited by the firm for the first time.[8] 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 a, $C^f_{a,s,t}$. Consequently, we define our new knowledge measure as:

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

[8] 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.

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.

4.2.3 Technology-level Myopia

We construct technology-level myopia in a similar fashion and with the same citation data as firm-level myopia. Here we measure the degree to which a firm's citations refer back to patents categorized in the same two-digit technology field as the patent that makes the citation. The greater a firm's share of citations that refer to patents in the same technology field as the citing patent, the greater the level of technological myopia. Specifically, if $C_{a,s}$ denotes the number of citations made by assignee a in year s and $C^{g}_{a,s}$ refers to those citations made by patents in technology field g to patents also in technology field g then the firm's level of technological myopia is defined as:

$$\text{TechnologyMyopia}_{a,g,s} = \frac{C^{g}_{a,s}}{C_{a,s}} \tag{1}$$

4.2.4 Location-level Myopia

Location-level myopia describes the degree to which patents produced within a given MSA cite patents produced in the same MSA. However, patents may have multiple inventors based in different locations. Consequently, to construct this measure we focus on the number of patent-MSA pairs that are cited and how many of these pairings involve the same MSA in which the citing patent was produced. For example, consider the case where a firm's stock of patents consists of one patent originating in the Ottawa MSA that cites two prior inventions. Further, assume that all of one of the cited patent's inventors are located in Boston while the second cited patent's inventors are located in San Francisco and Ottawa. In this case, our focal patent refers to three different MSA-patent pairs and self-cite their MSA once.

Consequently, our location-level myopia measure would equal one-third. More generally, if firm a's stock of patents originating in MSA l cite $C_{a,l}$ unique patent-MSA pairs of which $C^l_{a,l}$ of these pairs originated in l, then the Location-level Myopia measure is:

$$\text{LocationMyopia}_{a,l} = \frac{C^l_{a,l}}{C_{a,l}} \tag{2}$$

4.2.5 Temporal-level Myopia

Our temporal-level 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, $(gyear_x)$. Consequently, 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:

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

In contrast, the minimum citation lag is:

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

4.3 Market Structure of Innovation and Creative Myopia

Next we examine whether our measures of creative myopia are correlated with the market structure of innovation. For example, are inventors located in company towns more likely than inventors in other locations to build upon their own firm's prior art?

A comparison of mean values of assignee self-citation rates by company town patents versus those from other locations is suggestive that a larger fraction of the prior art used in company town inventions is drawn from the inventors' own firm (Table 2, Row 4). Specifically, the mean citation rate for company town patents is 14.4% compared to only 8.7% for other locations. However, this simple comparison of means may belie import 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 we 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.[9] We begin with the set of company town patents. These are patents where all inventors on each patent, in cases of multiple-inventor patents, are located in the same company town as each other. There are approximately 14,105 such patents. We then select a "control patent" for each company town patent using the following algorithm: 1) construct the set of patents that has the same three-digit USPC technology field as the focal patent (if this set is empty, then drop the focal patent from the sample); 2) drop patents from the control patent set that do not have the same application year (if the set is empty, then keep control patents that have application years one year before or after the focal patent; if the set is still empty, then drop the focal patent from the sample); 3) drop patents from the control set if any inventors are located in a company town (if the set is empty, then drop the focal patent from the sample); 4)from the remaining set select as the control the patent that is closest to the focal patent in issue year (in the event of a tie, select randomly). Given the construction of our matched sample, the potential exists that a given control patent is matched multiple times to different focal patents.

[9] We fully appreciate the critiques of this method presented in Thompson and Fox-Kean (2005) and Thompson (2006) and plan to increase the closeness of the match on secondary technology classifications in the next draft.

4.4 Multinomial Logit Model

To confirm the results of the matched pair analysis, and to control for other determinants of self-citation, we estimate a multinomial logit model for the probability of each cited-citing pair of patents in the sample being in one of the following mutually exclusive categories: (a) a self-citation within the same "laboratory," (b) a citation made by that laboratory to another entity within the same MSA, and (c) a citation to prior art developed outside the inventors' own MSA. In these regressions the main variables of interest are our measures of concentration within the local innovation market: either a dummy for company town or the Herfindahl-based measure of dispersion of patents across assignees described above. We also control for MSA size (total number of patents and population), the number of university patents, the technology class of the focal patent, the grant year of the cited and citing patents, and (in the spirit of the classic citation function approach) the number of potentially citable patents falling in categories (a) and (b).

4.5 Citation Functions

Citations functions are used to form expectations about the number of citations a particular set of patents T makes to a set of pervious patents S (Caballero and Jaffe (2002), Jaffe and Trajtenberg (2002)). We employ citation function analysis to further control for the underlying distribution of potential citations across technology fields, locations, inventing firms, and time.

In the production of new inventions, prior innovations are helpful if they are known to exist and if time or subsequent discoveries have not made them obsolete. Consequently, when considering how innovations from a given set of prior innovations S might contribute to the production of a subsequent cohort of patents, T, one must consider the probabilities that during the production of T the typical innovation $s \in S$ was:

1. Not obsolete; and,

2. Known

The probability that ideas from S are not obsolete in the production of T is given by,

$$e^{-\beta_1 Y(T,S)} \tag{3}$$

In expression (3) β_1 represents the rate at which ideas in cohort S become obsolete. This parameter may be a function of the particular cohorts under consideration. That is, β_1 may be a function of characteristics of S and T. As well, $Y\left(T,S\right)$ may denote for example the amount of knowledge accumulated between the production of S and T or simply the time elapsed between the production of these two sets of patents. The idea is that the further these two sets are apart in idea space or in time, the less relevant we expect S to be in the production of T.

The probability of whether or not an idea is known is related to whether the "good news" of an idea in set S has reached the producer(s) of innovations in T. Consequently the probability ideas in S have diffused to the producers of T is given by:

$$1 - e^{-\beta_2 X(T,S)} \tag{4}$$

In expression (4) the parameter β_2 connotes the rate of knowledge diffusion and $X\left(T,S\right)$ represents the time in which S has an opportunity to diffuse (i.e., the time between the production of S and T).

With these two components and the assumption that obsolescence and diffusion are independent, we can express the probability that a typical innovation $t \in T$ cites or builds on a typical innovation $s \in S$. This is given by:

$$a(t,s) = \alpha e^{-\beta_1 Y(T,S)} \left[1 - e^{-\beta_2 X(T,S)}\right] \tag{5}$$

In Equation (5), α represents a parameter that can express for example the willingness of producers of innovations in T to make use of innovations in S that are known of and not obsolete. (We will focus on this "willingness" parameter in our analysis of the NIH Syndrome.) Alternatively, α can represent the importance of innovations in cohort S in the production of innovations in T.

With Equation (5) we can form an expectation of the number of citations all patents in T will make to patents in S. We begin by looking at the total number of citations a typical patent in T will make to *all* patents in S. This is expressed as:

$$c\left(t,S\right)=a\left(t,s\right)N_{S}=\alpha e^{-\beta_{1}Y(T,S)}\left[1-e^{-\beta_{2}X(T,S)}\right]N_{S}$$

In the above equation N_S represents the number of patents in cohort S.

Lastly, the total number of citations all patents in T make to patents in S is given by:

$$c\left(T,S\right)=a\left(t,s\right)N_{T}N_{S}=\alpha e^{-\beta_{1}Y(T,S)}\left[1-e^{-\beta_{2}X(T,S)}\right]N_{T}N_{S} \tag{6}$$

where N_T represents the number of patents in cohort T.

For the purposes of investigating our research question we employ Equation 6. Here our parameters of interest are the estimated α's that control for effect of location on innovation. Specifically, we are interested in how these location α's vary with the dispersion of assignee innovative activity within a location. Recall, the α's reflect the extent inventors are willing to make use of certain ideas. In our case, this will be the extent to which inventors make use of their own prior art.

We begin by defining as a laboratory a pairing of an "assignee" firm, a, and the location, K, of its inventors. We denote this pairing simply as A. Our objective is to explain the number of citations A makes back to A's prior work.

We define for each citing patent I assigned to A the following characteristics:

- T: the grant year of a citing patent;
- G: the technology field of a citing patent; and,

- U: the technological class of a citing patent

Further, we define the following characteristics for A's patents that can be cited:

- t: The grant year; and,
- u: The technological class

The probability that any of A's patents characterized by $\{T, G, U\}$ cite any of A's patents characterized by $\{t, u\}$ is:

$$= \alpha_{K,T,G,t} P(U, u) e^{-\beta_1(T-t)} \big(1 - e^{\beta_2(T-1)}\big)$$

Consequently, the total number of citations made by A's patents fitting the $\{T, G, U\}$ profile to patents fitting the $\{t, u\}$, is:

$$E\big[C_{K,T,G,U,t,u}\big] = N_{K,T,G,U} N_{K,t,u} \alpha_{K,T,G,t} P(U, u) e^{-\beta_1(T-t)} \big(1 - e^{\beta_2(T-t)}\big)$$

Now we aggregate to the technology field level. That is, we sum up as follows:

$$\sum_U \sum_u E\big[C_{K,T,G,U,t,u}\big] = \alpha_{K,T,G,t} e^{-\beta_1(T-t)} \big(1 - e^{\beta_2(T-t)}\big) \sum_U \sum_u \Big[N_{K,T,G,U} N_{K,t,u} P(U, u)\Big]$$

Now we define $P(U, u)$. Let $P(U, u) = 1 + \gamma D(U, u)$ where $D(U, u)$ equals one when $U = u$ yields:

$$\sum_U \sum_u E\big[C_{K,T,G,U,t,u}\big] = \alpha_{K,T,G,t} e^{-\beta_1(T-t)} \big(1 - e^{\beta_2(T-t)}\big) \Big[N_{K,T,G} N_{K,t} + \gamma \sum_x N_{K,T,G,x} N_{K,t,x}\Big]$$

Finally, the regression equation we estimate is given by:

$$\frac{C_{K,T,G,t}}{N_{K,T,G} N_{K,t}} = \alpha_K \alpha_T \alpha_t \alpha_G e^{-\beta_1(T-t)} \big(1 - e^{\beta_2(T-t)}\big) \left[1 + \gamma \sum_x \frac{N_{K,T,G,x}}{N_{K,T,G}} \frac{N_{K,t,x}}{N_{K,t}}\right] + \varepsilon_{K,T,G,t,g}$$

4.6 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)).[10]

We compare the relative impact of inventions across location types using the matched sample method. We begin by constructing a sample that includes all patents assigned to the dominant company town firms where all inventors are located in the company town. There are 13,958 such patents. For each of these focal patents, we identify a control patent that matches the focal patent on application year and three-digit technology classification, resulting in a dataset with 27,916 observations.

5 Results

In this section, we report results on our two relationships of interest: 1) market structure of innovation and creative myopia and 2) creative myopia and impact on subsequent innovation. Overall, we find a positive correlation between market structure concentration and firm-level myopia (though not other types) but uncover no evidence of a correlation between myopia and impact.

5.1 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

[10]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).

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. Perhaps most interestingly, these data reveal that company towns have significantly less inventive activity than other locations, on average (1,917 patents compared to 4,018).

By construction company towns are less concentrated in terms of their market structure of innovation as measured by inventive activity across firms and inventive activity across technology fields (Rows 3 and 4).

Since our myopia measures are all based on citations to prior art it is useful to note that the mean number of citations made by the patents in our sample is approximately nine (Row 2). In terms of firm-level myopia, on average approximately 9% of the citations the inventors of a patent in our sample make are to prior art from their own firm. However, this percentage is significantly higher (14.4%) for the subset of patents that are from company towns, forshadowing the creative myopia of inventors from these locations (Row 5). Furthermore, approximately 64% of the prior art cited by the average patent is in the same technology field as the citing patent (Row 6). Also, approximately 30% of the prior art cited by the average patent is from the same MSA as the citing patent (Row 7). In addition, approximately 93% of citations made by a firm in a given year are to prior art the firm has never cited before (Row 8).

We provide further 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 (14.9% compared to 8.0%), company town inventors make only half the proportion of citations to prior art from the local MSA that was not developed by their own firm (2.3% compared to 5.2%). 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 (78% compared to 83%).

Finally, in terms of impact, the mean patent in our sample receives a citation from approximately 14 subsequent inventions (Table 2, Row 10).

5.2 Are Company Towns More Myopic?

We report the average values of our set of myopia measures for inventions from company towns versus those from other locations in Table 4. The results presented in the top panel (A) are based on a sample where the focal patents include only those by dominant firms in company towns. The lower panel reports results based on a sample that includes all patents from company towns. The results are similar across the two panels and so for simplicity we only discuss the top panel results.

The results in the first row indicate that the assignee self-citation rate is significantly higher for company town inventions than for those from other locations. In fact, the self-citation rate for company town inventions is 50% higher; on average, a quarter of all citations made by company town inventors are to prior art from their own firm. We interpret this result as suggestive that company town inventors are more myopic in the innovation process than those from other locations.

However, although they may be more myopic, we find no evidence that company town inventors draw any less widely from other technology fields. The results reported in Row 2 indicate that approximately one-third of the prior art cited is from technology fields outside of that of the focal patent, regardless of the type of location in which the invention was developed. This result remains remarkably consistent even when self-citations are dropped from the analysis (Row 8).

The results reported in Row 3 indicate that company town inventions draw 30% more of their share of prior art used 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 9), we see that these inventors draw only half the fraction of their prior art from other local inventors, as compared to 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.

The results reported in Row 4 indicate that 79% of the citations made by company town inventors are to prior art that their firm has not cited before. This is less than the 85% 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 5). In addition, the 6% 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 6 suggest that company town inventors are not disadvantaged in terms of access to new ideas. Although we have no data concerning the relative costs of knowledge access, we find no statistically significant difference between the average citation lag for inventors from the two types of locations. The mean duration between the focal and cited patents is approximately six years for both. Furthermore, we find that the newness of the most recent idea upon which an invention builds is also similar across the two locations (Row 7). These results persist even after we drop assignee self-citations from the sample (Rows 10 and 11).

To summarize, company town inventors are more myopic in the sense that they are more likely to build upon prior art from their own firm 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 patented by others. However, these inventors are not more myopic on other key dimensions. They are not more likely than others to build upon prior art from the same technology field in which they are working. Nor are they more likely to build upon prior art from their local area above and beyond their propensity to draw from their lab's own prior art. Finally, they build upon prior art that is equally current as that used by their counterparts in more industrially dispersed locations. Thus, we find no evidence of company town inventors building upon outdated ideas.

5.2.1 Multinomial Logit Results

The results from our multinomial logit regression, presented in Table 5, suggest a significant degree of myopia in company towns. Specifically, the table reports marginal effects after multinomial logit regression; all estimated marginal effects are significant at the 1% level or better, even with robust standard errors. All else equal, compared to a patent from a less concentrated MSA, a patent generated in a company town is almost 10% more likely to self-cite their own lab, slightly more likely to cite a patent generated elsewhere in the same MSA, and significantly less likely to cite a patent generated outside the MSA. Other MSA characteristics are also associated with citation patterns. Self-citation or local bias in citing outside the lab is higher in MSAs with more university-owned patents, but much lower in MSAs that are more technologically diversified. We are also actively exploring whether attributes of assignees drive citation patterns, mitigating or reinforcing the company town effect.

5.2.2 Market Structure and Myopia: Citation Function Analysis

Forthcoming.

5.3 Does Myopia Hinder Innovation Impact?

The findings we report above suggest that innovation in company towns is more myopic than that 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.

5.3.1 Myopia and Impact: Matching Method Analysis

We report the average number of citations received by inventions from company towns versus those from other locations in Table 6. Similar to the matched sample findings presented above, the results presented in the top panel are based on a sample where the focal patents include only those by dominant firms whereas the lower panel reports results based on a sample that includes all company town patents. Once again the results are similar across the two panels and so for simplicity we discuss only the top panel results.

The first row of this table shows that on average inventions from company towns receive 13.4 citations. The data in this row also show that this number is not significantly different from the number of citations received by inventions that are similar in nature but from other locations (i.e., not from company towns). In other words, the matched sample data provides no evidence that inventions from company towns have less impact on subsequent innovation.

Consistent with our prior results based on citations made, the second row of this table indicates that company town firms receive 2.28 times the number of self-citations. In other words, although there is no difference in the overall level of impact from inventions developed inside versus outside company towns, a much larger fraction of the impact is realized by the inventing firm itself in company towns. Row 3 indicates no difference between the inventions from these two types of locations in terms of the breadth of their impact across technology space, at least not at the two-digit classification scheme level. The results reported in Row 6 confirm that this result is robust to dropping assignee self-cites.

The results reported in the fourth row indicate that although inventions from copmany towns are likely to receive more self-citations, they are not likely to receive more citations from their own location overall. 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 even firms in industrially dispersed locations receive a significant fraction of their citations from their own MSA. Thus, although firms in industrially dispersed locations "lose" in terms of local self-citations relative to those in copmany towns, they seem to gain in terms of citations from other firms in their home location such that the average number of citations received from local firms is not significantly different across inventors from the two types of locations. The results reported in Row 7, where we drop assignee self-citations, confirm this intuition; comparing the number of citations received from local inventors, patents in industrially dispersed locations receive 2.5 times the number of citations as those received by company town inventions.

The results in the fifth row reveal that we find no significant difference in the breadth of geographic influence from inventions across the two types of locations. The average invention from either location type is subsequently cited by inventors from approximately five unique MSAs. This may include assignee self-cites from multiple locations in the case where firms conduct research in more than one location. However, when we drop assignee self-citations (Row 8), the result persists: the average number of unique MSAs that have built upon the focal invention falls, but the difference between locations remains insignificant. Thus, even though a larger fraction of the impact from copmany town inventions is realized by the inventing firm itself, the geographic scope of the impact from these inventions does not appear to be diminished.

5.3.2 Myopia and Impact: Citation Function Analysis

Forthcoming.

6 Conclusion

Company towns are an interesting feature of the geography of innovation: inventive activity in some locations is dominated by a single organization and this may have important implications for the economics of localized knowledge spillovers. We find that in these locations, the dominant firm tends to be more myopic than firms in locations where the local innovation market is less concentrated.

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 - and 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 and if this is true then the myopia we observe should have a negative effect on impact of these inventions. Interestingly, we see no evidence of this, at least as captured by the number of citations received by the patents belonging to the firms in our sample. Myopic inventors tend to produce patents that are less likely to be cited externally, but this is made up for by higher levels of internal citations. Furthermore, we find little evidence that the geographic breadth of citations to these firms' patents is diminished. Of course it may be that the economic value of patents that are disproportionately self-cited is lower, such that myopia does in fact have a negative impact. But this finding also points to potential benefits associated with "in group favoritism" as a mechanism supporting efficient internal exchange and co-ordination.

The forward citation patterns that we observe 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.

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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
Rochester (NY)	Kodak	chemicals	10,950	5,304	48.4	6,793	78.1
Albany (NY)	GE	electronics	5,255	3,773	71.8	9,073	41.6
Saginaw (MI)	Dow	chemicals	3,441	1,740	50.6	3,916	44.4
Baton Rouge (LA)	Ethyl Corp.	chemicals	2,010	718	35.7	836	85.9
Harrisburg (PA)	AMP	electronics	1,835	1,096	59.7	1,784	61.4
Ottawa (ON)	Nortel	computers	1,637	498	30.4	966	51.6
Rockford (IL)	Sundstrand	electronics	1,599	756	47.3	1,063	71.1
Boise City (ID)	Micron	electronics	1,344	558	41.5	576	96.9
Binghamton (NY)	IBM	computers	1,266	814	66.4	8,850	9.2
Johnson City (TN)	Kodak	chemicals	1,118	627	56.1	6,793	9.2
Melbourne (FL)	Harris	electronics	1,080	467	43.2	706	66.1
Peoria (IL)	Catepillar	mechanical	976	639	65.5	820	77.9

The sample is based on US patents issued to non-government organizations between 1985-1995, inclusive, where at least one inventor is located in the US or Canada.

Table 2: Descriptive Statistics

	All MSAs Mean	All MSAs Median	Company Towns Mean	Other Locations Mean
1. No. patents by MSA	3,668	1,392	1,917	4,018
	(5,470)		(2,421)	(5,845)
2. No. Citations Made	9.665	9.638	8.568	9.885
	(1.583)		(1.499)	(1.517)
Diversity				
3. Assignee	0.871	0.935	0.550	0.935
	(0.163)		(0.149)	(0.053)
4. Technological	0.916	0.931	0.841	0.931
	(0.050)		(0.086)	(0.014)
Self-Citation				
5. Assignee	0.097	0.091	0.144	0.087
	(0.047)		(0.073)	(0.034)
6. Technological	0.641	0.639	0.652	0.638
	(0.034)		(0.057)	(0.028)
7. MSA	0.301	0.290	0.377	0.286
	(0.117)		(0.182)	(0.094)
Percentage of New Citations				
8. All Citations	0.929	0.928	0.928	0.929
	(0.016)		(0.024)	(0.014)
9. Excluding Self-Citations	0.930	0.927	0.934	0.930
	(0.014)		(0.022)	(0.013)
10. No. Cites Rcvd by Patent	14.294	13.449	14.763	14.200
	(4.589)		(8.101)	(3.612)

Standard deviations in parenthesis

Table 3: Decomposition of Prior Art

	Citations Made	MSA Self-Cites Assignee Self-Cites	MSA Self-Cites Assignee Non-Self-Cites	MSA Non-Self-Cites Assignee Self-Cites	MSA Non-Self-Cites Assignee Non-Self-Cites
Absolute Number					
All Patents	8.805	0.645	0.430	0.356	7.375
Company Towns	8.474	1.158	0.206	0.433	6.676
Other Locations	8.834	0.601	0.449	0.349	7.435
Share of Citations					
All Patents	9.046	0.086	0.050	0.041	0.823
Company Towns	8.650	0.149	0.023	0.048	0.780
Other Locations	9.081	0.080	0.052	0.041	0.827

Table 4: Creative Myopia: Company Towns versus Other Locations

	Matched Pairs (I)	Company Towns (II)	Other Towns (III)	Difference (II) - (II)	t-statistic
A. Dominant Firm Patents Matched (Company Towns)					
Self-Citation Rate					
1. Assignee	12,652	0.25	0.16	0.10***	4.01
2. Technology	12,652	0.67	0.66	0.01	0.86
3. MSA	12,652	0.22	0.17	0.05***	2.48
Percentage of New Citations					
4. All Citations	13,709	0.79	0.85	-0.07***	-4.91
5. Excluding Self-Citations	13,709	0.81	0.86	-0.05***	-4.88
Citation Lag (Years)					
6. All Citations	12,651	6.05	6.36	-0.31	-1.28
7. To Most Recent Patent	12,651	1.72	2.71	-.099	-1.49
Excluding Assignee Self-Citations					
Self-Citation Rate					
8. Technology	11,371	0.66	0.65	-0.01	0.71
9. MSA	11,371	0.03	0.07	-0.04***	-2.48
Citation Lag (Years)					
10. All Citations	11,370	6.44	6.48	-0.04	-0.16
11. To Most Recent Patent	11,370	2.85	3.10	-0.24	-0.32
B. All Company Town Patents Matched					
Self-Citation Rate					
12. Assignee	20,708	0.24	0.15	0.08***	4.29
13. Technology	20,708	0.66	0.66	0.002	0.18
14. MSA	20,708	0.22	0.17	0.05***	2.14
Percentage of New Citations					
15. All Citations	21,737	0.81	0.86	-0.05***	-3.18
16. Excluding Self-Citations	21,737	0.84	0.88	-0.03***	-2.68
Citation Lag (Years)					
17. All Citations	22,856	6.17	6.52	-0.35	-1.51
18. To Most Recent Patent	22,856	1.68	2.63	-.095	-1.61
Excluding Assignee Self-Citations					
Self-Citation Rate					
19. Technology	18,760	0.65	0.65	0.001	0.07
20. MSA	18,760	0.04	0.07	-0.03***	-2.13
Citation Lag (Years)					
21. All Citations	20,366	6.50	6.70	-0.20	-1.12
22. To Most Recent Patent	20,366	2.88	2.98	-0.10	-0.19

Standard errors clustered at the MSA level. *** = significant at 1%

Table 5: Marginal Effects in Multinomial Logit Regression

	Outcome = self-cite	Outcome = cite another entity in same MSA	Outcome = cite outside MSA
E[y]	13.04%	9.21%	77.74%
Dummy =1 if "Company Town"	0.01***	0.003***	-0.013***
MSA population (millions)	0.004***	0.003***	-0.004***
Number of University patents (1000s)	0.001***	0.040***	-0.044***
MSA technology dispersion	-0.284***	-0.136***	0.420***
Number of "self" patents available to cite	0.00005***	-0,00002***	-0,00002***
Number of non-self patents available to cite in MSA (1000s)	0.0000001***	0.0000001***	0.0000003***
Citing year effects	x	x	x
Cited year effects	x	x	x
Technology class effects	x	x	x

Robust standard errors. *** = significant at 1%. N = 1408,697

Table 6: Impact Measured by Citations Received

	Matched Pairs (I)	One-Horse Towns (II)	Other Towns (III)	Difference (II) - (III)	t-statistic
A. Dominant Firm Patents Matched (Company Towns)					
Includes Assignee Self-Citations					
1. Total Citations Received	13,958	13.36	13.03	0.33	0.22
2. Self-Citations Received (same Assignee)	13,958	3.41	1.50	1.92***	2.25
3. Citations Received from Same Technology	13,958	7.92	7.42	0.50	0.52
4. Citations Received from Focal MSA	13,958	3.69	3.13	0.56	0.68
5. Number of Unique Citing MSAs	13,958	4.71	5.04	-0.33	-0.71
Excludes Assignee Self-Citations					
6. Citations Received from same Technology	13,958	5.79	6.46	-0.67	-0.93
7. Citations Received from Focal MSA	13,958	0.58	1.46	-0.89***	-3.06
8. Number of Unique Citing MSAs	13,958	4.03	4.67	-0.64	-1.53
B. All Company Town Patents Matched					
Includes Assignee Self-Citations					
9. Total Citations Received	25,386	12.78	12.91	-0.12	-0.12
10. Self-Citations Received (same Assignee)	25,386	3.01	1.45	1.56***	2.97
11. Citations Received from same Technology	25,386	7.61	7.36	0.25	0.34
12. Citations Received from Focal MSA	25,386	3.22	3.33	-0.11	-0.16
13. Number of Unique Citing MSAs	25,386	4.82	5.11	-0.29	-0.95
Excludes Assignee Self-Citations					
14. Citations Received from same Technology	25,386	5.79	6.46	-0.67	-0.93
15. Citations Received from Focal MSA	25,386	0.75	1.57	-0.82***	-2.63
16. Number of Unique Citing MSAs	25,386	4.06	4.75	-0.69***	-2.43

Standard errors clustered at the MSA level. *** = significant at 1%

Figure 1 – Market Structure of Innovation

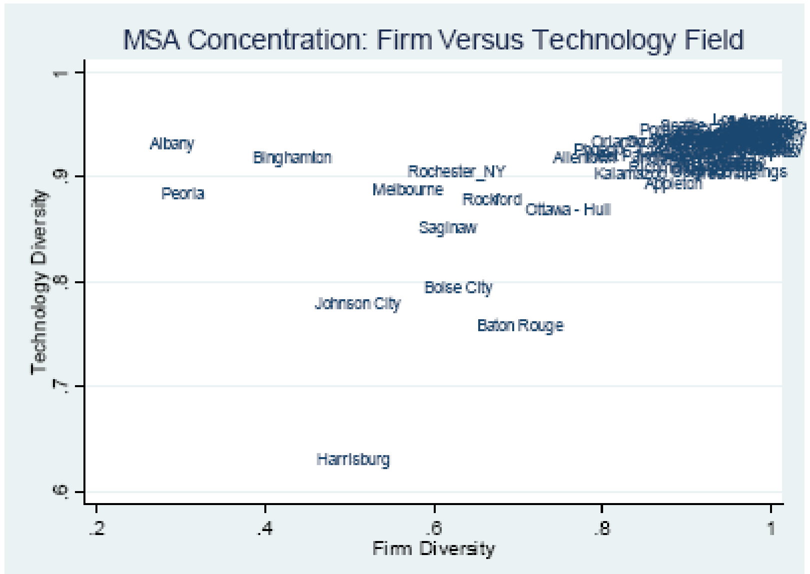

Figure 2 – Map of Company Towns