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Abstract

In this article, we use regional-scale data on global patenting by large and small firms to analyze regional resilience. Building on Markusen’s industrial districts framework (1996), we develop a typology of innovation districts, categorizing regions into four types based on the percent of small firm patents and overall patent rate. We then explore implications of this new typology for regional income, technological diversity, and for understanding the relationship between innovation ecologies and regional resilience. We then propose testable hypotheses that build off this framework and form the basis for a new research program on innovation ecologies and regional resilience.

JEL: Classifications:

R11, R58, O32

1. Introduction

In theoretical discussions on regional resilience, the importance of entrepreneurialism (small firm activity) and innovation (embedded regional research and development capacity) have risen to the forefront. However, empirical evidence increasingly indicates that institutional capacities and firm networks are more critical to the ability of regions to manage transition than those factors measured by "innovation metrics" alone (Foster 2006; Treado and Giarratani 2008).

To understand "the resilient region" requires a sober look at patterns of growth and decline in local economies and a revisiting of how we understand sustainable regional economies (Chapple and Lester 2007). A similar task was required in order to understand why some places were "sticky" in global economy, retaining firms and jobs, and others "slippery spaces," losing established specializations as production decamped for alternate locations (Markusen 1996).

In this article, we set out to engage the question of regional resilience by merging the recent methodological approaches and innovation measures with established analytical work on industrial districts. We used this grounded approach to refine our understanding of innovation ecologies and how these may relate to regional resilience. We also develop a set of testable hypotheses with the goal of generating a research program to further our understanding of regional resilience and the role of small firms, regional institutions, and how the ecology of firm types affect resilience.

In this analysis, we use data on "triadic" patents (US, Japan, and Europe) to measure regional innovation, both per capita and categorized by firm size for regions in the US (the 365 MSAs, metropolitan statistical areas). We then use this data to adapt Markusen's "typology of industrial districts" to create a "typology of innovation districts," categorizing the 81 regions with more than ten triadic patents into four categories based on these two variables (Markusen 1996). In addition, and in keeping with the framework of Markusen's industrial districts analysis, for these 81 regions we incorporate data on regional income and on regional industry concentration (in our case, technology concentration). The result is an analysis which is both a challenge to and confirmation of existing theory.

2. Linking Resilience and Innovation: The Path from Industrial Districts to Learning Regions

Discussions of regional development are shifting from a focus on growth and development to the analysis of the relative resilience of regional economies in response to rapid transitions in technologies, markets, and exogenous economic shocks. This emphasis on sustainable regions rather than economic competitiveness extends research on learning regions and the "innovative milieu" to a broader conceptualization of embedded institutional adaptive capacities. It also revisits the use of natural systems models as frameworks for understanding economic growth and distribution (Swanstrom 2008; Clark and Christopherson 2009).

As innovation has become more central to economic development, the question of how regions become places in which innovation thrives and high-technology industries grow, has emerged to dominate both theory and practice in planning and policy. Among academics, the theory of the "learning region" developed as an adaptation of the industrial districts framework for the knowledge economy. The learning region model makes two arguments explicit. First, agglomeration economies alone are not sufficient to guarantee the kind of ongoing innovation essential to firm success in a world with short product cycles and heightened global competition. Second, innovation requires a skilled and creative regional labor market operating under entrepreneurial conditions (Gertler and Wolfe 2002). "The challenge of 'learning regions' is to increase the innovative capability of SME-based industrial agglomerations through identifying 'the economic logic by which milieu fosters innovation' (Storper, 1993)." However, empirical evidence to date on which "innovative milieus" produce places with the capacity to both innovate and commercialize is limited by the data. The resilience discussion emerges into this uncertain debate about the role of small firm innovation and entrepreneurialism in developing long-run adaptive capacities in regions.

It has become foundational in economic geography that firms co-locate in order to share common infrastructure and labor markets, to take advantage of locally-embedded technologies, production processes, and institutions, and to reduce transportation and transaction costs (Clark, Feldman et al. 2000). The theory is rooted in a discourse which recognizes the power of regional path dependencies, the importance of specialized regional labor markets, and the dominance of embedded and localized institutional networks (Christopherson and Clark 2007). This literature draws its empirical grounding from a body of "critical case studies" in regional studies, economic geography, and sociology (Storper and Christopherson 1987; Florida and Kenney 1992; Saxenian 1994; Treado and Giarratani 2008). In recent years, the theory of agglomeration economies has been expanded and applied to not only the spatial organization of production but the spatial distribution of innovation as well (Moulaert and Sekia 2003; Boschma 2005; Simmie 2005). The development of frameworks such as industry clusters, learning regions, and territorial innovation systems have gradually shifted from a discussion of co-location of producers (often connected through value-chains) to the co-location of innovators. The innovators are often assumed to mimic the spatial logic of the producer model.

However, empirical evidence, both from critical case studies and from an emerging quantitative literature, indicates that the geography of innovation differs from the spatial distribution of production. In particular, since one of the key inputs to innovation---knowledge---is seen as a public good that is widely dispersed, the comparative advantage of regions in terms of resource (i.e. information) access is more difficult to explain. And, yet, much prior research finds that information flows, even of published information, are geographically constrained (Jaffe, Trajtenberg et al. 1993; Feldman 1999; Gertler 2003). This nuanced analysis has led to a broader debate about both the theory and the metrics used to analyze innovation processes and patterns.

The industry clusters thesis, popularized by Michael Porter and based in theories of agglomeration economies and corollary geographic arguments regarding economies of scale and scope, articulates a vision of regional innovation set in motion by spillover effects and "untraded interdependencies" (Porter 1990; Storper 1997). Agrawal and Cockburn developed the "anchor tenant" hypothesis that argues that the presence of large, R&D (research and development) intensive firms generates positive regional externalities for small firms in the same sector, including improved access to university research from that region (Agrawal and Cockburn 2003). Drawing on this literature, the clear economic development strategy is to establish, through policy, a dynamic set of collective assets for the purpose of building small firm innovation capacity in the region.

To the extent it is recognized, the limits to regional innovative capacity have been explained with reference to endogenous characteristics of the region, such as inadequate supportive institutions and/or technological or political "lock-in" (Todtling and Trippl 2005). These approaches, although providing significant insights, leave a model of cooperation, collaboration, and trust among firms as the norm rather than the exception. In this lack of attention to power dynamics, and emphasis on trust and "soft infrastructure," the literature on regions and firm networks is afflicted by some of the same theoretical problems as those which afflict the concept of social capital (Markusen 1999; DeFillipis 2001).

And yet, the industrial district model, derived largely from empirical work in Italy, has never been an easy fit in the US (Storper and Walker 1989; Gray, Golob et al. 1996). In part, the variation in regulation at the state level and general decentralization of regulation makes the regional differentiation at the scale of the state a significant difference between the US and other countries (Gilson 1999; Befort 2003; Stone 2004). The decentralization of US industrial policy means that, while other industrialized and industrializing countries have had advantages in terms of national-scale targeted industrial policy, with the possible exception of defense, US industries enjoy ad hoc political and policy advantages rather than a sustained position as a national economic priority (Markusen 1991).

Thus, counter arguments and alternative hypotheses have recently gained ground. These arguments focus on political, legal, and policy environments which shape regional economies and the role of firm strategies in establishing rules, norms, and power asymmetries within firm networks (Dicken and Malmberg 2001; Pike 2009). While industry cluster effects build on the idea of a "commons" (in skills, knowledge, institutions), in the US, a culture of competitiveness which privileges property rights over collaboration works against this notion of developing a commons as a path to shared innovation and economic growth. Using evidence from firms operating in Silicon Valley and Route 128, Florida and Kenney demonstrated that US firms, even when agglomerating do not reap the advantages of geographic proximity expected from the industrial district paradigm. Instead they focus on establishing organizational practices which produce captive suppliers and competition based on cost rather than quality of innovation (Florida and Kenney 1990).

Ron Boschma has pointed out that the relationship between proximity and innovation itself is somewhat under-theorized. He argues that physical proximity is not the only type of proximity at work in regional firm ecologies or firm networks. Dis-aggregating "proximity" into institutional, social, conceptual, cognitive, and geographic, Boschma argues that physical proximity produces both positive and negative outcomes for firms and networks, with implications for regional resilience. In balancing risks and costs of production (and innovation), geographic proximity reduces uncertainty and solves coordination problems while at the same time producing lock-in and introducing unintended spillover effects (Boschma 2005). Thus, the consequences for small firms embedded in agglomeration economies can be decidedly mixed. The assumption that geographic proximity to large firms or a location in a highly concentrated firm network benefits small firms and increases regional resilience (adaptive capacity) is increasingly contested in theory and subject to evaluation in empirical work.

While the study by Florida and Kenney was published fifteen years ago, the question of how regions in the US "innovate" remains a controversial question in management, policy, and economic development. Florida and Kenney responded in their article to the compelling argument made by Annalee Saxenian in her book, *Regional Advantage* (Saxenian 1994). Saxenian provided initial evidence for the flexible production in the US context, and a successful example of the emergence of high-technology regions. In part, her analysis foreshadows a framework for regional innovation systems, based on a model shaped by the original empirical work presented by Piore and Sabel in 1984 and the "possibilities for prosperity" that their flexible specialization model proposed for regional economies (Piore and Sabel 1984). Applying that model for innovation and flexible production in the United States has been an ongoing empirical and theoretical project with many iterations adapted for both traditional industrial and high-technology contexts (Markusen, Hall et al. 1986).

In our approach, we revisit the typologies of industrial districts described by Ann Markusen in her 1996 article, *Sticky Places in Slippery Space*. While Markusen focused on identifying "industrial districts" and delineating their distinct characteristics, we have approached these regional economies from the perspective of "innovation districts" with an eye toward identifying factors relevant to resilience rather than growth alone.

3. Regional Resilience and Industrial Districts

In both cases---industrial districts or innovation districts---the empirical analysis of regions and the attempt to categorize them follows from an extensive theoretical discussion about the character and evolution of regional economies and their relative position in the national and global markets. These analyses have sought to both accurately describe the current position of regional economies and also to provide some predictive basis for understanding future prospects (and possible policy interventions). In recent years, the discussion of future prospects has evolved into a debate about reactive capabilities, absorptive capacity, and regional resilience (Chapple and Lester 2007; Pendall, Foster et al. 2007; Swanstrom 2008).

These terms effectively describe the endogenously-developed assets of the region which determine (at least in part) the ability to react and adapt to short-run exogenous shocks or long-run exogenous shifts in markets. Thus, these concepts attempt to describe a similar set of ideas which illustrate a significant shift in regional economic development theory, policy, and practice from an export-oriented approach focused on investment in basic industries to an approach that privileges investments in institutional capacities and indigenous institutions (Pike, Rodríguez-Pose et al. 2006)

In this emerging model, small firms tend to play a critical role. Small firms are seen as engines of new ideas and new employment. Indeed, the discussion of small firm innovation and entrepreneurship has become central to discussions in economic development and science and technology policy. Empirical approaches to measuring small firm activity have varied. Some researchers (often from business or policy disciplines) have focused heavily on entrepreneurship, start-up firms, and technology transfer. Thus, the literature has focused on the localizing mechanisms for information flows, such as labor mobility (Saxenian 1994; Agrawal and Cockburn 2003; Agrawal, Cockburn et al. 2006). Economic geographers and economic sociologists have emphasized questions of proximity, innovation, and the social, institutional, and cultural dynamics which link regional economies in a networked web of “untraded interdependencies.”

The memory of the debates in the early 1990s, among economists and geographers, about the relatively minor role of small firms in regional employment, has largely been forgotten. Few researchers seek to engage (much less test) Ben Harrison’s argument of “the small firm myth” which calls into question the rhetorical emphasis on small firms and the policies which take them for-granted (Harrison 1994; Harrison 1994). However, several hypotheses have emerged which expand the debate about small firms in regional economies and particularly, their role in regional innovation systems and regional resilience (Rutherford and Holmes 2008).

In this article, we look again at the question of small firms and innovation within the context of these broader debates. We revisit the role of small firms as an element of the underlying capacities which produce (or sustain) regional resilience over time through an empirical analysis of US regions with exceptional records of innovation activities. We have found the four types of industrial districts Markusen originally identified as a useful starting point for developing a typology of innovation ecologies.

We use the term, “innovation ecologies,” to encompass the variations in the mix of small and large firms, levels of innovation, technology mixes and institutional infrastructures observed in our analysis. The overall project is to develop a greater understanding of how different innovation ecologies affect regional resilience. Many potential proxy measures for resilience have developed, including employment levels, income distribution and growth, patent rates, the presence of recognizable “industry clusters,” regional GDP, and various measures of firm performance (individual and networks). We will use regional (MSA) GDP per capita as an initial measure of regional income, but in the concluding section, we discuss other potential measures.

In her seminal work on regional industry structure and economic development, Markusen identified four categories of industrial districts using several measures to differentiate the characteristics of the industries (1996):

1) Marshallian industrial districts are characterized by a large percentage of small firms, with significant levels of cooperation among small firms in the district. This form parallels Porter and the *Italian* districts are the canonical case.

2) Hub-and-spoke districts are dominated by oligopolistic large firms. These districts should have good income distributions and generally are dominated by a single industry (or related set of industries). Auto industry clusters (Detroit, MI, Nagoya, Japan) are key examples.

3) Satellite industrial platforms are also large firm dominated, but tend to be more heterogeneous by industry, as they consist of an agglomeration of branch plants of externally headquartered firms. Both high and low income versions are likely. Many sunbelt industrial cities have this structure.

4) State-anchored industrial districts are dominated by a government and/or university employer. Madison, WI and Columbus, OH are examples, as are many cities with large defense installations.

In subsequent analyses, initial concerns expressed about the dominance and power asymmetries of the hub-and-spoke and satellite industrial platforms have increased as industry-specific case study evidence indicates Marshallian industrial districts, composed of flexibly specialized and innovative small firms, are the exception rather than the norm. In addition, the fourth category, state-anchored districts, has recently emerged as a category less linked to direct production subsidies and more anchored to universities and research centers. We will use the Markusen typology as a starting point for analyzing innovation ecologies based on triadic patenting rates and the distributions across firm sizes.

4. Methodology, Data Sources and Analysis

Our methodology involves a spatial analysis of inventions that resulted in “triadic” (US-Japan-Europe) patents. We use multiple variables: firm size, location, and technology class to build on the recognized typology of industrial districts through the use of this new data, focused on innovation and commercialization rather than production.

For our analysis, we use a random sample of 9060 triadic patents drawn from the population of 32,390 triadic patent families in the OECD database having an invention priority between 2000 and 2003 and at least one US addressed inventor. Here, a triadic patent is a patent from a patent family that contains a US granted patent and a European Patent Office and Japanese Patent Office patent application. Firms that apply for triadic patents are understood as those that are not only innovative, but also that view their market as “global” (i.e., spanning three major economic regions). The USPTO patent database includes a field designating patents as belonging to “small entities” (independent inventor, a small business concern [generally less than 500 employees for manufacturing], or a nonprofit organization), which we use, along with assignee data, to code inventors as belonging to large firms versus small firms or university/non-profit research organization patents for the spatial analyses. Our dataset contains data on the full sample, and spans all populated technology classes, allowing us to examine clusters across a variety of technologies (i.e., not limited to only, for example, nanotechnology or biotechnology). The triadic patent data includes the street location of the inventor, allowing a much more detailed analysis compared to using only the city and state information the USPTO public database provides.[1]

We then used boundary files for metropolitan statistical areas (defined by US Census 2000 data) to determine the number of triadic patents that fell into a given region. We then calculated two geographic variables to assess regional innovation capacity and activity of innovative small firms: 1) the per capita triadic patents for each region and 2) the percentage of triadic patents in a region attributable to small firms (excluding non-profit and universities). We then mapped these patents (based on the location of the inventor) and assigned them to metropolitan statistical areas. Of the 365 MSAs identified in the 2000 Census data, 81 MSAs included ten or more triadic patents. From these 81 MSAs we calculated the two MSA-level variables we used to categorize the regions: 1) triadic patents per capita (2000 population), which ranged from 0.008 to 1.011 (per 1000), with a mean of 0.07 and 2) the proportion of small firm triadic patents to total triadic patents per region (excluding university and non-profit assignees), which ranged from 0 percent to 30 percent with a mean of 10.71 percent.

Motivated by prior work on industrial districts and regional resilience, we used these variables to develop our typology and to categorize regions according to a novel typology of innovation ecologies. In addition, we used regional income data from the Bureau of Economic Analysis’ Regional Income and Economic System and the patent NBER technology class data from our patent database to test two additional aspects of the innovation districts hypotheses: 1) whether regions with more small firm innovation have higher incomes and 2) to what extent technology clustering influences outcomes (rankings) for innovation districts.[2]

Our choice of datasets presents some important limitations that have to be kept in mind when interpreting the results. One important limitation of this approach is that patents are a noisy measure of innovation (Cohen, Nelson et al. 2000; Cohen, Goto et al. 2002; Agrawal and Cockburn 2003). Not all inventions are patented, and patent propensities

[1] The USPTO generated an MSA-level analysis using data from the 1990s. Our data is both more recent and covers these more “competitive” patents. Also, our data attaches location to the inventor rather than the firm so the geographies produced represent the innovative capacity of regions as a function of the regional labor market capacities rather than the firm headquarters.

[2] See Gross Domestic Product by Metropolitan Area Metropolitan area annual estimates, Regional Economic Accounts Bureau of Economic Analysis, U.S. Department of Commerce. http://www.bea.gov/regional/index.htm#gsp

vary by industry, firm size and firm strategy (Kortum and Lerner 1999; Cohen, Goto et al. 2002). In addition, our use of the triadic patent data creates important limitations to our study. One advantage of using the triadic patent database for our measure of inventions is that this allows us to focus on more economically important patents. A random sampling of all US patents would result in large numbers of economically unimportant patents (Scherer and Harhoff 2000). Filing in multiple jurisdictions works as a threshold, limiting our study to patents that are likely to have a higher minimal economic value.

On the other hand, this means that this sample of patents is a select subset of inventions, and even of patented inventions. Our sample is likely to over-sample commercialized inventions (which makes it especially useful for comparing commercialization rates across regions, but not useful as an estimate of the base rate of commercialization across all inventions). Also, perhaps, the sample is biased against nonprofit, small, and/or independent inventors, although the discounts for "small entities" in the US and other patent offices may ameliorate some of these effects. Thus, we can think of this as a conservative estimate of small firm innovation (since small firm inventions may be under-represented in our sample), targeting more economically important and globally marketed inventions (note that, through licensing, it may be a large firm that is globally marketing the innovation). Overall, while there are important advantages to using the triadic patent data, there are also limitations of this strategy.

Insert Map 1

5. Ecologies of Innovation

We begin with our map of our two key MSA-level measures: triadic patents per capita and small firm share of triadic patents (see Map 1). We can see that per capita invention rates are high in regions such as San Francisco and Boston, consistent with much of the literature on "high-tech" regions (Saxenian 1994). However, we also see high rates of triadic patents per capita in regions such as Minneapolis, Rochester, Cincinnati and Madison. We see that the rate of small firm inventions varies significantly across these high-tech regions, with, for example, a relatively high percentage of these patents coming from small firms in Boston, San Francisco and Madison on the one hand, and relatively few small firm patents in Minneapolis, Rochester and Cincinnati. We also see that both new sunbelt cities and old industrial cities are found on the high and the low ends of both of our measures. Thus, we argue that there is a need to develop a typology of innovation ecologies that moves beyond "high-tech", rustbelt v. sunbelt, or other existing ways of categorizing regions.

Using Markusen's typology of industrial districts as the starting point (and filtered through the competing hypotheses in the literature such as power asymmetry, anchor-tenant, and university-centered), we have categorized the 81 US regions in our triadic patent set into a four-fold typology of “innovation ecologies”. These four ecologies are displayed in Table 1, numbered counter-clockwise.[3]

Type 1: Consistent with Marshallian industrial districts (San Francisco, Madison): These regions have a high proportion of overall patents and a high proportion of small firm patents. These are similar to the classic “high-tech” industrial districts, although we see many state-centered/university-centered regions as well (see below).

Type 3: Consistent with Marshallian industrial directs but less successful (St Louis, Toledo):
These regions have a low proportion of overall patents and a high proportion of small firm patents. While these regions still have many small firms, they are not as innovative as either Type 1 or Type 2a (large firm centered high-tech).

Type 2: Consistent with Power Asymmetries hypothesis:

2a) Hub and Spoke District or Anchor-Tenant (Rochester, Cincinnati):
These regions have a high proportion of overall patents and a low proportion of small firm patents. These regions are still high-tech (many patents per capita), but with a relatively less active small firm sector. These may be regions where one or a few dominant large firms have been able to capture the local innovation infrastructure and leverage power asymmetries to capture a larger share of the inventions growing out of the local information space, or these large firms may be better able to capitalize on distant information, relative to their smaller neighbors.

2b) Satellite Platform (Columbus, San Antonio):
These regions have a low proportion of overall patents and a low proportion of small firm patents. Note that while this type includes high population growth regions such as San Antonio, Jacksonville and Charleston these regions have very little inventive activity and very few small firm inventors among those inventions (note that this is among the 81 most innovative MSAs of the 365 total MSAs). We suspect that such regions may be more vulnerable to economic pressures pushing down wages and tax revenues.

Type 4: The University/Research Center anchored-district (a variation on Markusen’s State-Anchored Districts) (Madison, Raleigh-Durham-Chapel Hill):
These regions have a high number of university and non-profit patents. We expect this type to overlap with Type 1 (high-tech regions with many innovative small firms).

[3] Appendix Table 2 gives the data for all 81 MSAs, including patents per capita, percent of small firm patents, percent of patents in the dominant technology class (and name of most common 2-digit NBER technology class), Herfindahl index of technology concentration, 2000 population, and income (GDP per capita by MSA)

These four types (plus the university centered type) of innovation ecologies can serve as the starting point for a series of hypotheses and empirical tests of the relations between innovation ecology and regional resilience. We introduce some preliminary analyses in this section. In the conclusion, we discuss future work that can further develop this research program.

Insert Table 1

Technological Diversity

We begin with an analysis of the technology diversity/homogeneity of the regions. Here, we have contrasting expectations. On the one hand, regional diversity is seen as an important basis for resilience, making a region less dependent on the fate of a single industry (with Detroit and Youngstown being cautionary tales). On the other hand, the classic literature on flexible specialization/industrial districts (Piore and Sabel 1984; Porter 1990; Asheim 1995) emphasizes the learning benefits that come from specialization in a set of related industries and technologies. To explore the relations between our innovation ecologies and technology diversity, we examine the technology diversity of our four types. This question of technological diversity, while relevant to all four categories in the typology, was particularly critical in understanding the difference between the Type 2a: *Hub and Spoke regions* and Type 2b: *Satellite Platform regions*.

In keeping with the industrial districts model, we hypothesized that the Type 2a*: Hub and Spoke regions* would be more dominated by a single technology or industry class while the Type 2b*: Satellite Platforms regions* would show greater diversity. On the other hand, the industrial districts model does not provide a clear hypothesis regarding Type 1*: Marshallian regions* and Type 3*: Less Successful Marshallian regions*. Still, we suspect that Type 1 regions would be more diversified than Type 3 districts in general, although Type 1 regions with smaller populations may have less diversity (Drennan 2002).

In our analysis of regional technology concentration and diversity we calculated two measures of technology concentration and dispersion. The first measure was based on a Herfindahl index of the triadic patents in the region based on NBER technology class and the second measure was of technology dominance for the region using the same data (see Table 2). The dominant index represents the proportion of triadic patents attributed to a single 1-digit NBER technology category. The higher the number is, the greater the presence of one technology class in a region. The Herfindahl index, on the other hand, shows the concentration ratio of technology classes in each region, accounting for the spread across all classes. If the share of the six NBER classes is evenly distributed, then H index would be low (= 0.1667). On the other hand, if the region is monopolized by one technology, then the H index would be 1. The results are presented in Table 2.

Insert Table 2

As we expected, *Hub and Spoke regions (Type 2a)* tend to have higher levels of technology concentration than do *Satellite Platform regions (Type 2b)*. For example, the mean H index is 0.35 in Type2a and 0.25 in Type 2b. The effect is more obvious in smaller MSAs. For instance, if we compare New London and Dayton, the biggest technology class in both regions is drugs but New London has 78 percent of concentration rate and very concentrated (H index = 0.65); while in Dayton the drug industry only accounts for around 30 percent of the total inventions (H=.19).

On the other hand, when we compare Type 1 and Type 3, we do not see a clear pattern. For example, when grouping by dominant technology, we can find comparisons in both directions. In surgical instruments dominant regions, Boston (Type 1) is less concentrated than Miami (Type 3). On the other hand, in two regions dominated by communication technology, San Diego (Type 1) and Charlotte (Type 3), San Diego (H=.31), is slightly more concentrated than Charlotte (H=.22). Thus, we find Marshallian districts with relatively high and low levels of concentration among both the high innovation and lower innovation regions.

Regional Income

We also examined the relative income levels across our four types. Here, prior work gives a fairly clear guide, with the expectation that Type 2a: *Hub and Spoke regions* would have higher incomes and Type 2b: *Satellite Platform regions* would have lower incomes. The question of regional incomes has implications for questions of regional resilience in term of equity and quality of life measures.

To evaluate the question of income levels, we looked at the MSA GDP per capita for each type of innovation districts (see Table 2 and Table 3). Figure 1 gives the results of the average regional GDP for each type. We hypothesized that the *Satellite Platform* (Type 2b) regions would have the lowest GDP and that is what we see. However, we did not anticipate that any of these innovation districts (again, a set of the most innovative 81 MSA in the US) would have a GDP below the national average for all MSAs. This finding is consistent with some theories of agglomeration economies and regional labor markets, in particular, the argument that resilient regions are not those with rapid growth trajectories but those able to mitigate unanticipated variations in labor and other localized factor costs (Clark 2004; Chapple and Lester 2007).

Insert Table 3

We also find that Type 1 *Marshallian Innovation Districts* have the highest average regional GDP per capita, consistent with a policy focus on replicating the success of high-tech regions with many innovative small firms. The fact that the lesser Marshallian districts (i.e., those with relatively many small firm innovators, but fewer patents per capita) have higher average GDP per capita than do either of the large-firm dominated districts (even the high-tech ones in Type 2a) suggests that large firm dominance may hurt regional resilience, even if it generates high rates of innovation.

6. Conclusions and Policy Implications: What it Means for Regional Resilience

In broad terms, we found that the typology of industrial districts, integrating recent counter arguments and modified through the use of innovation metrics, presented several hypotheses that held through the empirical analysis. Type 1: *Marshallian regions*, characterized by many innovative small firms, do well on a variety of metrics (especially income). However, this category was surprisingly small in number of regions (7 out of 40). Further, of the seven regions in Type 1: *Marshallian regions*, four also qualified for Type 4: *State-anchored regions* based on their high levels of university and non-profit patenting.   Unfortunately, this finding complicates the university-based technology transfer policy model of regional innovation systems and its implications for ensuring resilient institutional models. From this data, it is not clear whether university and non-profit research and development produces better measures in regions where small firms are already doing well or whether the state sponsored R&D programs actually promote small firm innovation.

Perhaps the most interesting findings from this analysis concerns Type 2a: *Hub and Spoke regions* and Type 2b: *Satellite Platforms regions*. These categories are defined by the lower level of small firm patenting relative to Type 1: *Marshallian regions* and Type 3: *Less Successful Marshallian regions*. We also see that these large-firm dominated regions have relatively low regional GDPs per capita. This suggests that ecologies with many innovative small firms may be more resilient, which further suggests that policies that encourage small firm innovation have important benefits for regional economies.

Our typology and initial results raise several other questions that can be tested in order to further develop our understanding of the effects of innovation ecologies on regional resilience. Our future work will push this analysis beyond the stage of measuring inventions to look at the commercialization of patented technologies, and how variations in innovation ecologies (including the four types, as well as measures of technology concentration, and local infrastructure) affect the rates of commercialization, especially among small firms.

In addition, while we have seen that Type 2 ecologies are dominated by large firms, the more interesting issue, for theory and policy, is how these two types (Hub and Spoke v. Satellite Platform) are distinguished from each other by the overall per capita rate of patenting. One central hypothesis is that large firms in a particular technology or industry sector encourage entrepreneurship in that same sector among co-located small firms (Porter 1990). However, there is also a counter-argument that within “industry clusters” power asymmetries between members of the firm network produce differential access to specialized labor markets (including entrepreneurs and inventors) and research and development infrastructure (including university-based centers). Empirical evidence indicates that large firms can stifle the development of innovative small firms in the same industry and within the same regional economy (Christopherson and Clark 2007a; Rutherford and Holmes 2008).   In other words, the spillover effects of firm networks are not always positive for all firms (Boschma 2005).

The argument that “power in firm networks,”---the dominance of large firms within regional economies, compromising the ability of small firms to access specialized labor markets and research and development infrastructure---does not stipulate that the large firms need to be local or foreign. For example, Type 2b*: Satellite Platforms regions* may be less resilient because their innovation capacity is not embedded in the region but instead rests with their (distant) parent firm. Similarly, Type 2a: *Hub and Spoke regions* may be less resilient because local large firms co-opt the innovations of the small firms that do exist in the region (Christopherson and Clark 2007a). Interestingly, this analysis indicates that these models of regional production and innovation---in which large firms exert considerable dominance---may be remarkably sustainable (or resilient) over time. However, as models for income growth, they may be considerably less desirable.

In fact, the negative effects for small firms and for the overall regional economy of co-location with large firms, appears to be underestimated in both theory and policy. It is not clear, however, which "proximities," as Boschma might describe it (e.g. institutional, social, geographic, etc…), are driving these negative effects. If regional innovation and income growth depend on the presence of an active small firm network with an ability to both innovate and move forward to production, better estimates of the downside risks of proximity are necessary for policy. In both political and policy rhetoric it is typical to hear the call for support and maintenance of small firms as the backbone of the national economy both as innovators and as job producers. However, much academic debate swirls around these claims, often pointing out that public policy both over-subsidizes large firms and under-subsidizes small firms, while understanding the relative position of neither in the broader world economy (Harrison 1994; Harrison 1994).

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Table 1: Regions (MSAs) with Greater than 10 Triadic Patents Categorized by Triadic Patent Rank Per Capita and Proportion of Small Firm Patents (2003)

	Top 20 Regions with High Levels of Triadic Patents Per Capita	**Bottom 20 Regions with High Levels of Triadic Patents Per Capita**
High Rate of Small Firm Triadic Patents (greater than 10% of total)	Type 1: Large MSAs[4]: 1. San Diego, CA 2. Boston, MA 3. San Francisco--Oakland--San Jose, CA Medium MSAs: 4. Raleigh--Durham--Chapel Hill, NC Small MSAs: 5. Fort Collins, CO 6. Madison, WI 7. Santa Barbara, CA	Type 3: Large MSAs: 1. Tampa--St. Petersburg, FL 2. Miami--Fort Lauderdale, FL 3. Washington--Baltimore, 4. St. Louis, MO—IL Medium MSAs: 5. West Palm Beach, FL 6. Memphis 7. Greensboro--Winston-Salem--High Point, NC 8. Orlando, FL 9. Sacramento, CA 10. Kansas City, MO—KS 11. Providence, RI—MA 12. Salt Lake City, UT 13. Charlotte, NC Small MSAs: 14. Toledo, OH 15. Norfolk, VA
Low Rate of Small Firm Triadic Patents(less than 10% of total)	Type 2a: Large MSAs: 1. Minneapolis--St. Paul Medium MSAs: 2. Rochester, NY 3. Austin 4. Cincinnati Small MSAs: 5. New London 6. Albany 7. Florence, SC 8. Elmira, NY 9. Burlington, VT 10. Parkersburg, OH--Marietta, WV 11. Corvallis, OR 12. Saginaw, MI 13. Boise City, ID	Type 2b: Large MSAs: N/A Medium MSAs: 1. Jacksonville, FL 2. Columbus, OH 3. San Antonio, TX Small MSAs: 4. Dayton, OH 5. Charleston, SC 6. South Bend, IN

[4] MSA Size categories (Small MSA: under 1million population 2000, Medium MSA: 1-2 million population 2000, Large: over 2 million population 2000)

Table 2. Attributes of US "innovation districts"
(regions have more than 10 triadic patents 2000 to 2004)

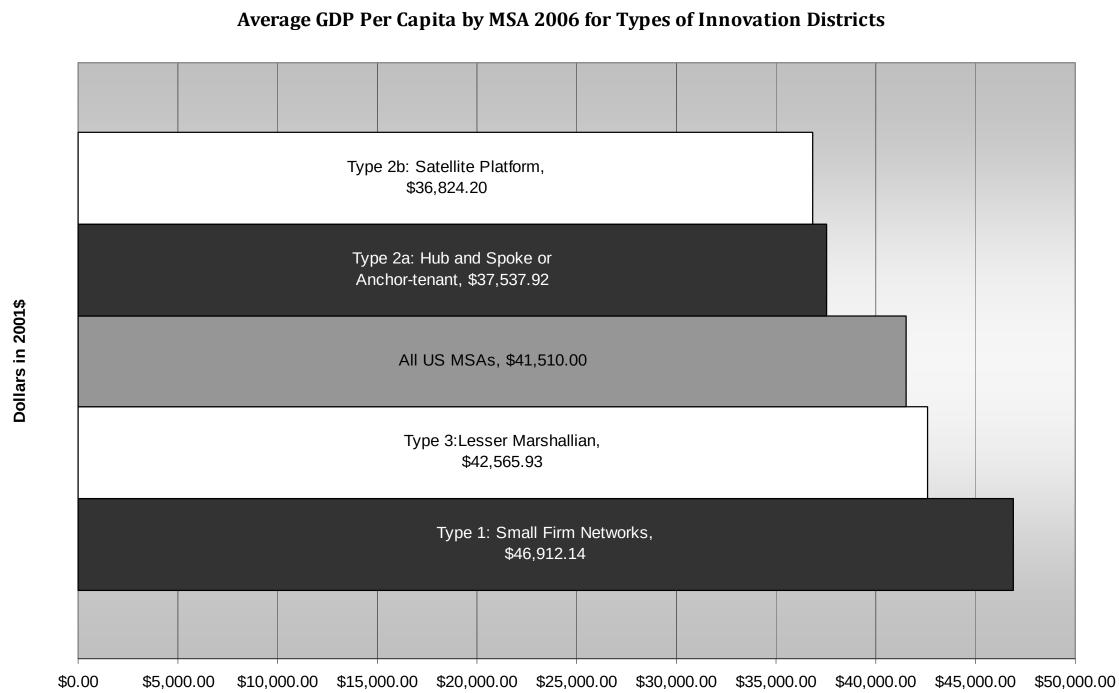
MSAs (>10 patents)	% of Small Firm Patents[5]	Patent per capita (1K)	Dominant	HHI	2000pop	MSA GDP per Capita 2006	Dominant technology class	Type
Raleigh--Durham--Chapel Hill, NC	13.79%	0.082	0.31	0.21	1,187,941	$42,435	Biotechnology	type1
Madison, WI	19.05%	0.082	0.37	0.26	426,526	$48,353	Biotechnology	type1
New York--Northern New Jersey--Long Island, NY--NJ--CT--PA	10.02%	0.041	0.26	0.2	21,199,865	$53,706	Drugs	
St. Louis, MO--IL	19.15%	0.018	0.27	0.31	2,603,607	$36,953	Drugs	type3
San Antonio, TX	7.69%	0.011	0.5	0.22	1,592,383	$31,940	Drugs	type2b
Providence--Fall River--Warwick, RI--MA	27.78%	0.016	0.32	0.24	1,188,613	$34,065	Drugs	type3
Dayton--Springfield, OH	5.26%	0.022	0.29	0.19	950,558	$35,900	Drugs	type2b
New London--Norwich, CT--RI	0.00%	0.167	0.78	0.65	293,566	$39,800	Drugs	type2a
Kalamazoo--Battle Creek, MI	0.00%	0.068	0.58	0.42	452,851	$30,260	Drugs	
Huntsville, AL	n.a	0.029	0.4	0.28	342,376	$42,035	Drugs	
Boston--Worcester--Lawrence, MA--NH--ME--CT	16.85%	0.081	0.27	0.19	5,819,100	$55,943	surgery	type1
Miami--Fort Lauderdale, FL	31.03%	0.008	0.42	0.25	3,876,380	$40,277	Surgery	type3
Tampa--St. Petersburg--Clearwater, FL	25.93%	0.012	0.24	0.19	2,395,997	$35,402	Surgery	type3
Salt Lake City--Ogden, UT	21.88%	0.024	0.48	0.3	1,333,914	$45,603	Surgery	type3
Greensboro--Winston-Salem--High Point, NC	19.05%	0.017	0.33	0.23	1,251,509	$41,337	Surgery	type3
Memphis, TN--AR--MS	16.00%	0.022	0.64	0.47	1,135,614	$41,916	Surgery	type3
Reading, PA	0.00%	0.027	0.3	0.24	373,638	$30,071	Surgery	
Appleton--Oshkosh--Neenah, WI	0.00%	0.064	0.26	0.22	358,365	$35,801	Surgery	
Los Angeles--Riverside--Orange County, CA	25.39%	0.025	0.23	0.18	16,373,645	$46,919	Communication	
Chicago--Gary--Kenosha, IL--IN--WI	10.94%	0.029	0.22	0.17	9,157,540	$45,057	Communication	
Washington--Baltimore, DC--MD--VA--WV	31.54%	0.019	0.32	0.21	7,608,070	$60,757	Communication	type3
San Francisco--Oakland--San Jose, CA	13.68%	0.152	0.49	0.25	7,039,362	$61,895	Communication	type1
Dallas--Fort Worth, TX	9.33%	0.029	0.37	0.25	5,221,801	$49,702	Communication	
San Diego, CA	18.42%	0.112	0.35	0.31	2,813,833	$47,156	Communication	type1
Denver--Boulder--Greeley, CO	14.94%	0.034	0.46	0.28	2,581,506	$50,729	Communication	
Charlotte--Gastonia--Rock Hill, NC--SC	23.81%	0.014	0.33	0.22	1,499,293	$63,668	Communication	type3
West Palm Beach--Boca Raton, FL	16.00%	0.023	0.31	0.21	1,131,184	n.a	Communication	type3
Melbourne--Titusville--Palm Bay, FL	8.33%	0.05	0.75	0.59	476,230	$28,852	Communication	
Hickory--Morganton--Lenoir, NC	10.00%	0.029	0.5	0.36	341,851	$29,613	Communication	
Elmira, NY	0.00%	0.154	0.36	0.28	91,070	$25,570	Communication	type2a
Seattle--Tacoma--Bremerton, WA	19.23%	0.046	0.43	0.26	3,554,760	$54,082	Software	
Phoenix--Mesa, AZ	13.95%	0.04	0.33	0.23	3,251,876	$40,065	Software	
Santa Barbara--Santa Maria--Lompoc, CA	25.81%	0.088	0.36	0.32	399,347	$40,098	Software	type1
Provo--Orem, UT	n.a	0.027	0.3	0.24	368,536	$21,946	Software	
Fort Collins--Loveland, CO	10.81%	0.155	0.38	0.25	251,494	$32,505	software	type1
Portland--Salem, OR--WA	7.08%	0.05	0.47	0.31	2,265,223	$45,615	computer peripherals	

[5] % of small firm = # of small firm patent / total patent within MSA, where numbers of small firm patent is counted by excluding university/government lab patents.

MSAs (>10 patents)	% of Small Firm Patents[5]	Patent per capita (1K)	Dominant	HHI	2000pop	MSA GDP per Capita 2006	Dominant technology class	Type
Lexington, KY	7.69%	0.031	0.33	0.25	479,198	$44,573	computer peripherals	
Corvallis, OR	2.53%	1.011	0.52	0.37	78,153	$48,709	computer peripherals	type2a
Austin--San Marcos, TX	4.76%	0.07	0.43	0.31	1,249,763	$42,904	semiconductor	type2a
Colorado Springs, CO	17.65%	0.033	0.59	0.45	516,929	$32,346	semiconductor	
Boise City, ID	2.70%	0.086	0.35	0.27	432,345	$38,627	semiconductor	type2a
Houston--Galveston--Brazoria, TX	9.73%	0.027	0.58	0.38	4,669,571	$48,176	misc/chemical	
Minneapolis--St. Paul, MN--WI	6.48%	0.13	0.28	0.19	2,968,806	$50,231	misc/chemical	type2a
Cincinnati--Hamilton, OH--KY--IN	2.34%	0.109	0.29	0.2	1,979,202	$38,514	misc/chemical	type2a
Kansas City, MO--KS	31.82%	0.013	0.35	0.26	1,776,062	$42,947	misc/chemical	type3
Columbus, OH	5.56%	0.015	0.39	0.23	1,540,157	$43,703	misc/chemical	type2b
Hartford, CT	8.64%	0.069	0.26	0.2	1,183,110	$51,475	misc/chemical	
Rochester, NY	0.91%	0.403	0.3	0.22	1,098,201	$37,032	misc/chemical	type2a
Evansville--Henderson, IN--KY	0.00%	0.037	0.73	0.57	296,195	$37,210	organic compound	
Parkersburg--Marietta, WV--OH	0.00%	0.073	0.64	0.54	151,237	$27,526	organic compound	type2a
Philadelphia--Wilmington--Atlantic City, PA--NJ--DE--MD	10.19%	0.052	0.47	0.3	6,188,463	$46,796	Resins	
Cleveland--Akron, OH	6.62%	0.052	0.26	0.21	2,945,831	$25,944	Resins	
Pittsburgh, PA	4.29%	0.032	0.35	0.23	2,358,695	$38,651	Resins	
Albany--Schenectady--Troy, NY	1.38%	0.17	0.34	0.25	875,583	$36,523	Resins	type2a
Charleston--North Charleston, SC	8.33%	0.022	0.42	0.32	549,033	$33,503	Resins	type2b
Johnson City--Kingsport--Bristol, TN--VA	4.17%	0.05	0.54	0.35	480,091	$25,811	Resins	
Saginaw--Bay City--Midland, MI	1.59%	0.159	0.66	0.48	403,070	$30,038	Resins	type2a
Lancaster, PA	13.33%	0.032	0.4	0.3	470,658	$31,615	elec lighting	
Sacramento--Yolo, CA	27.27%	0.012	0.27	0.22	1,796,857	$38,869	electrical devices	type3
Harrisburg--Lebanon--Carlisle, PA	0.00%	0.027	0.82	0.7	629,401	$41,972	electrical devices	
York, PA	0.00%	0.029	0.73	0.57	381,751	$29,493	electrical devices	
Allentown--Bethlehem--Easton, PA	7.50%	0.063	0.53	0.34	637,958	$29,876	gas	
Tucson, AZ	16.13%	0.043	0.36	0.24	843,746	$27,769	info storage	
Burlington, VT	0.00%	0.094	0.56	0.46	169,391	$43,638	info storage	type2a
Jacksonville, FL	0.00%	0.015	0.38	0.28	1,100,491	$39,075	mat proc&handling	type2b
Toledo, OH	25.00%	0.019	0.75	0.6	618,203	$34,945	mat proc&handling	type3
Indianapolis, IN	5.08%	0.037	0.24	0.19	1,607,486	$46,995	misc/elec	
Norfolk--Virginia Beach--Newport News, VA—NC	11.76%	0.012	0.63	0.44	1,569,541	$36,449	misc/mechanical	type3
Grand Rapids--Muskegon--Holland, MI	25.93%	0.025	0.59	0.41	1,088,514	$37,458	misc/mechanical	
Richmond--Petersburg, VA	3.45%	0.029	0.31	0.23	996,512	$41,961	misc/mechanical	
Canton--Massillon, OH	0.00%	0.034	0.57	0.38	406,934	$26,971	misc/mechanical	
Atlanta, GA	12.71%	0.03	0.25	0.19	4,112,198	$44,971	misc/others	
Greenville--Spartanburg--Anderson, SC	0.00%	0.052	0.38	0.29	962,441	$34,233	misc/others	
Florence, SC	0.00%	0.119	0.4	0.34	125,761	$28,881	misc/others	type2a
Detroit--Ann Arbor--Flint, MI	6.49%	0.044	0.43	0.25	5,456,428	$40,757	motor engine	
Milwaukee--Racine, WI	6.10%	0.049	0.37	0.22	1,689,572	$44,923	nuclear/x-ray	
Orlando, FL	18.75%	0.01	0.35	0.27	1,644,561	$42,735	power systems	type3
Buffalo--Niagara Falls, NY	2.50%	0.035	0.32	0.21	1,170,111	$31,590	power systems	

MSAs (>10 patents)	% of Small Firm Patents[5]	Patent per capita (1K)	Dominant	HHI	2000pop	MSA GDP per Capita 2006	Dominant technology class	Type
Albuquerque, NM	15.79%	0.029	0.67	0.47	712,738	$37,696	power systems	
Peoria--Pekin, IL	7.14%	0.04	0.36	0.3	347,387	$37,260	power systems	
South Bend, IN	0.00%	0.041	0.43	0.24	265,559	$32,082	coating chemical	

Table 3: Average GDP per capita for Types of Innovation Districts



Map 1: MSAs with High Rates of Triadic Patents Per Capita and Rates of Small Firm Triadic Patents