New Business Clustering in U.S. Counties, 1990-2006

by

Lawrence A. Plummer
University of Oklahoma
Price College of Business
&
Wyckoff Consulting, LLC

for

Under contract no. SBAHQ-08-Q-0023

Release Date: May 2010

New Business Clustering in U.S. Counties, 1990-2006

by

Lawrence A. Plummer
University of Oklahoma
Price College of Business
&
Wyckoff Consulting, LLC

for

Office of Advocacy
www.sba.gov/advo

Under contract no. SBAHQ-08-Q-0023

Release Date: March 2010

This report was developed under a contract with the Small Business Administration, Office of Advocacy, and contains information and analysis that was reviewed and edited by officials of the Office of Advocacy. However, the final conclusions of the report do not necessarily reflect the views of the Office of Advocacy.

Contents

Executive Summary

The prescription for regions to position their economies strategically by supporting entrepreneurial activity in particular sectors is, of course, far from easy or simple to put into practice. In the absence of specific evidence, this paper maps county-level establishment birth data from 1990 to 2006 to explore where, and to what extent, new firms concentrate geographically. It uses econometric methods to determine the county-level factors of new firm formation. Summary statistics reveal some interesting geographic aspects of entrepreneurship by county and industry. There were nearly 5 single-unit establishment births per 1,000 workers during the study period within a range of zero and 28.49 births per 1,000 workers. Given the dominance of retail trade in the U.S. economy, it is not surprising that this industry sector has the highest rate of new firm births (1.06 births per 1,000 workers), followed closely by the "local market" industries (1.03 births per 1,000 workers).

In raw counts, Los Angeles, Cook (Chicago), and New York counties have the highest levels of entrepreneurial activity. Rankings by the rate of firm births per 1,000 workers in each given sector suggest that the nation's interior and northwestern counties—especially in states like Colorado, Utah, Washington, and others—had the highest levels of entrepreneurial activity per person during the study period. This finding is consistent with the level of westward migration over the last two decades. The mapping and spatial analysis indicate that entrepreneurial activity concentrates geographically. The entrepreneurial lows of the nation's Rust Belt states and the entrepreneurial highs of the Rocky Mountain regions are evident. A pivotal determinant for this pattern appears to be changes in county population. The spatial analysis indicates several pockets of significant start-up activity, including manufacturing in the Pacific Northwest; retail trade and local market industries in the Rocky Mountain States; high technology industries in California, Massachusetts, and North Carolina; extractive industries in Texas, Oklahoma, and Wyoming; business services in New York, Washington, DC, and Florida; and distributive industries in the plains states.

The econometric findings in this study indicate that the high technology sector is a special case. The sector proves the exception in the relationship between the rate of new firm births and changes in population, the creation of new knowledge, and the educational attainment of the county population. Moreover, the findings indicate that the fascination of scholars and policymakers with places like Silicon Valley, Boston's Route 128, and North Carolina's Research Triangle is deserved. Equally interesting is the business services sector. In fact, the high correlation between the firm birth rates in these two sectors and the evidence that both rely on an educated workforce implies a close link. It may be that the formation of new business service firms occurs partly as a response to high technology entrepreneurial activity.

Among the central findings of this study is that the fascination of scholars and policymakers with high technology start-up activity is justified in the sense that the pattern and determinants thereof stand apart from the patterns in other sectors. In addition, the level of entrepreneurial activity in one county seems to reinforce the level in nearby counties. In short, aligning the development goals and activities of a group of neighboring counties may be a necessary condition for encouraging entrepreneurial activity in any given county.

List of Tables

List of Figures

Introduction

Entrepreneurship, especially new business creation, is both a cause and consequence of economic growth. Although the odds are against the survival of most new ventures, those that survive the early liabilities of the resource-limited start-up phase contribute to a chaotic, albeit generally positive, economic dynamic by ushering out obsolete practices and introducing new products and new business models. Several communities in the United States have well-established reputations for being especially hospitable to the creation and growth of new firms, and a few high technology regions—including Silicon Valley, Boston's Route 128, and North Carolina's Research Triangle—are a constant source of fascination for policymakers, business leaders, and academics around the world. Of these regions, Silicon Valley is of central interest as many communities seek to emulate its entrepreneurial successes and economic prosperity.

Not every region can hope to be a hot spot of high technology entrepreneurial activity. It seems unlikely, for example, given the history of places like Silicon Valley, that a community can become the next high technology cluster without a solid research university. Moreover, from an economic welfare perspective, not every community *should* aspire to be the next high technology region, given that the national economy is more likely to benefit from entrepreneurial activity in a range of business sectors and product segments. Indeed, the premise of strategic positioning—in which competing businesses endeavor to distinguish themselves from their rivals—seems especially relevant in a regional context. That is, municipal or county planners, economic development authorities, and business leaders may find it advantageous to encourage the formation of new businesses in sectors or industries best suited to and sustained by extant local conditions, institutions, and resources.

The prescription for regions to position their economies strategically by supporting entrepreneurial activity in particular sectors is, of course, far from easy or simple to put into practice. Indeed, such a strategy incurs the problems and very real dangers of "picking winners" and necessarily requires the formulation of industrial policies typically shunned in the United States. Such fundamental normative issues are beyond the scope of the current paper, which instead follows a far more positivist path by exploring the extent to which regions—in this case, the counties that constitute the lower 48 United States—specialize in entrepreneurial activity in particular sectors and the determinants of such specialization. In many respects, this study complements Armington and Acs' (2002) study on regional variations in new firm formation, but also extends their work by focusing on individual counties rather than labor market areas (LMA) and analyzing the geographic patterns of entrepreneurial activity in the contiguous United States.

Given its focus, this study has two objectives. First, it employs spatial data analysis tools to identify where, and to what extent, new firms concentrate geographically using county level establishment birth data from 1990 to 2006. The analysis tools provide a statistical test for the geographic clustering of entrepreneurial activity and allow this clustering to be shown in a series of maps. Second, the paper explores many of the regional determinants of new firm formation identified by Armington and Acs (2002), but at a county level of analysis using econometric methods that account for the spatial autocorrelation of the data.[1] Indeed, where Armington and Acs's (2002) data encompass 394 labor market areas (LMAs), the data for this study cover more than 3,000 counties, thus dramatically enhancing the statistical power and inference of the findings.

The paper is organized as follows. The next section briefly reviews the relevant literature on these topics and explicitly states the hypotheses to be tested. The third section describes the study's research design including specifics on the data, the variable calculations, the empirical model, and the spatial data analysis methods used to assess the location of entrepreneurial activity in the United States. The fourth section reports the findings of the statistical and spatial analysis, including a summary and descriptive statistics of the data, maps indicating the locations of entrepreneurial activity by industry sector, and regression results for the hypothesis testing. The fifth section discusses some of the implications of findings for practice, policy, and future research. The final section offers a few concluding remarks.

Literature Review and Hypotheses

Why do regions differ in their levels of entrepreneurial activity (Shane & Venkataraman, 2000)? Evidence suggests that new firms, especially those in knowledge-intensive industries, tend to concentrate geographically, are more likely to fail as a result, and yet, in the case of the survivors, tend to outperform similar firms operating in more isolated locations (McCann and Folta, 2008). The question, of course, is why. Is it because some regions, in addition to possessing sound legal, capital, and physical infrastructures, offer more supportive cultures or effective leadership (Venkataraman, 2004)? Is it because the process of creative destruction operates principally on a local level (Pe'er & Vertinsky, 2008)? Is it because local socioeconomic conditions including the human capital of an area's workforce (Armington & Acs, 2002), entry barriers, and the externalities found in highly concentrated areas (McCann & Folta, 2008) vary regionally? Perhaps it is all of these factors, but a core problem in most related studies is the presumption that new (as well as existing) firms *actually* cluster.

With this in mind, consider Cooper and Folta's (2000) pivotal question: to what extent do start-ups concentrate in particular regions? Almost as a rule, most scholars, policymakers, and regional business leaders take as given the premise that start-ups cluster geographically, despite some evidence to the contrary. Dumais, Ellison, and Glaeser (2002), for example, decompose dynamic changes in industry clusters into plant entries, expansions, and closures by new and existing firms using metropolitan statistical area (MSA) data. They find that new firm plants actually have a "de-agglomerating" effect in that these entries generally locate away from current geographic centers of industry. In other words, the clustering of new firms may be more apparent than real.

[1] A spatial autocorrelation principle recognizes that data collected at any position will have a greater similarity to or influence on those locations within its immediate vicinity. In other words, the data are spatially dependent.

Of course, determining whether or not new firms cluster requires that a related question be addressed (Cooper and Folta, 2000: 351): "What are ways to identify clusters, to classify them and to measure differences across them?" Fortunately, empirical measures of spatial clustering are available for answering this question. Doh and Hahn (2008), for example, provide an excellent introduction to both *global* and *local* indicators of spatial autocorrelation that indicate the degree and location of clustering. Their application of these techniques to data on the geographic distribution of firms in China's provinces (Chang & Park, 2005) is readily extended, as will be demonstrated in this paper, to analyzing the clustering of start-up activity. Likewise, Plummer (2010) offers a primer on the application of these techniques to the study of new firm formation.

Another question posed by Cooper and Folta (2000) is "What are the processes that lead high technology firms to locate in clusters?" Again, posed more simply, why do new firms start where they do? What are the determinants of a particular region's level of start-up activity? As can be imagined, a range of theories and studies suggest an array of explanations:

- Proximity of a research university (Zucker, Darby, & Armstrong, 2002),
- Availability of venture capital (Sorenson & Stuart, 2001),
- Spatial distribution of entrepreneurial opportunities (Sorenson & Audia, 2000),
- Availability of tangible and intangible resources (Ahuja & Katila, 2004; Russo, 2003),
- Availability of labor (Acs & Armington, 2004a; Marchington, Carroll, & Boxall, 2003; Rumelt, 1987; Song, Almeida, & Wu, 2003),
- Availability of knowledge (Acs & Armington, 2004b; Almeida, 1996; Almeida & Kogut, 1999; Almeida & Phene, 2004; Chung & Alcácer, 2002; DeCarolis & Deeds, 1999; Gibbons, 2004; Phene & Almeida, 2003),
- Munificence of local institutional environments (Audretsch, 2000; Baum & Oliver, 1996; Casson, 2003; Mugler, 2000; Storey, 2000), and
- Quality of local supporting infrastructure (Lomi, 1995; Sorenson, 2003).

Few studies have explored the determinants of new firm geographic concentration at the national level. A key exception, a study by Armington and Acs (2002), reports ordinary least squares (OLS) estimates from a standard linear model using data from 394 labor market areas (LMAs) in the United States. with the number of firm births per worker as the dependent variable. Arguing that population growth contributes to demand externalities in labor markets, they find that the rate of population growth is positively associated with the rate of new firm births. In addition, as evidence of the importance of local entry barriers, they find that areas that are home to larger businesses—indicated by local employment divided by the number of establishments—have lower start-up rates. Finally, consistent with the premise of start-ups relying on an educated and technically skilled workforce (as well as the skills of the entrepreneur), they find start-up rates are higher in areas where the share of the adult population holding at least a college degree is greater.

As with any study, there is reason to examine Armington and Acs' (2002) anew with updated theory and enhanced methodology. First, recent theoretical advancements have led to the knowledge spillover theory of entrepreneurship (Acs, Audretsch, Braunerhjelm, & Carlsson, 2005; Audretsch, Keilbach, & Lehmann, 2006), in which the creation of new firms is offered as the missing link between new knowledge and economic growth. Aside from contributing to the enhancement of endogenous growth theory (Romer, 1986, 1987, 1990), the knowledge spillover theory of entrepreneurship incorporates the newest thinking and empirical evidence concerning the *spatial* dimension of economic activity (cf. Anselin, Varga, & Acs, 2000; Varga, 1998, 2000). Second, from a research methodology standpoint, Armington and Acs's (2002) analysis may be adversely affected by spatial dependence in their data, as well as the small sample size relative to what is possible with county-level data. For the remainder of this paper, regions are equated with counties.

A Model of Entrepreneurial Activity

Entrepreneurship is the process by which enterprising individuals pursue and exploit profitable opportunities to introduce products, processes, and/or business models that are new to the market or that create new markets entirely (Shane & Venkataraman, 2000; Venkataraman, 1997). At the heart of this process is the intersection of alert individuals and the market imperfections judged by these individuals to offer greater economic returns, if corrected, than other income streams available to them (e.g., working for an existing firm). While this process does not necessarily result in the formation of new firms, the difficulty existing firms have in adapting and expanding to satisfy an economy's growing needs suggests that new venture creation is the crucial contributor to a region's growth and prosperity (Audretsch et al., 2006). From this point of view, the essence of an individual's entrepreneurial choice is starting their own business versus offering their labor to an incumbent enterprise (Parker, 2004). Indeed, it can be assumed that those who choose to become entrepreneurs have judged that the returns from doing so will exceed the returns from earning a wage as the employee of an ongoing concern.

From a regional perspective, this entrepreneurial choice framework suggests that—holding the characteristics of individuals constant—the level of new firm formation in a region increases with the number of opportunities and decreases with the local burdens or barriers to the entrepreneurship process. Indeed, the knowledge spillover theory of entrepreneurship (Audretsch et al., 2006) suggests the following model of entrepreneurial activity for a given region or county *i*,

$$\mathrm{E}_i = (1/\beta_i)(\pi^*[g_y, \mathrm{A}_{\mathrm{opp},}\, \theta]_i - w_i) \qquad (1)$$

where $\pi^*[g_y, A_{opp}, \theta]$ is the returns expected from exploiting those opportunities arising from regional growth (g_y) and investment in new knowledge (A_{opp}) not already exploited by incumbent firms (θ), w are wages to be earned by working for an incumbent firm, and β represents institutional barriers and resource constraints other than incumbent firms.

The Hypotheses

The knowledge spillover model given by Equation 1 has two critical implications. First, the model implies that the spatial distribution of entrepreneurial activity in the economy is neither random nor uniform. That is, regional variations in the conditions that facilitate and impede entrepreneurial activity necessarily suggest regional variation in levels of entrepreneurial activity. In fact, the knowledge spillover model suggests that entrepreneurial activity *concentrates* across regions, especially if one thinks of regions in terms of contiguous administrative units like counties or census tracts. The reason is that any region (i.e., county, state, or census tract) is not a self-contained area of economic or entrepreneurial activity, as the relevant activities in one region spill over into another. More formally, the level of opportunities in a given county *i* feed the level of entrepreneurial activity both within the county and in the adjacent county *j*.

The regional concentration of entrepreneurial activity appears as a positive correlation in the levels of entrepreneurial activity across regions; that is, the level in one region or county is positively associated with the level in an adjacent area. This model is, of course, virtually a statement of fact in high technology clusters like Silicon Valley, given that the entrepreneurial progress in Santa Clara County has also boosted the economic well-being of the greater Bay Area. The model, however, has rarely been explored empirically and, thus, the following hypothesis will be tested:

> Hypothesis 1: The level of entrepreneurial activity in a given county *i* is positively associated with the level of entrepreneurial activity in the set of neighboring counties *J*.

Second, the spillover model also suggests a number of factors that determine the level of entrepreneurial activity within the region. That is, an increase or decrease in the level of any one factor will lead to a corresponding change in the level of entrepreneurial activity. As mentioned, the model suggests four broad categories of factors that determine the level of entrepreneurial activity in the region. The first two sets of factors are the entrepreneurial opportunities that come from the economic growth of the region and the distinct contribution of new knowledge. That is, as the size of the region's economy grows and the stock of knowledge in the region expands, so too should the number of new businesses expand. These first two groups of factors seem rather straightforward:

> Hypothesis 2: The level of entrepreneurial activity in a given county *i* increases with higher levels of economic growth within the county.

> Hypothesis 3: The level of entrepreneurial activity in a given county *i* increases with increases in the stock of knowledge within the county.

Third are the region's entrepreneurial barriers that either limit the number of available opportunities (i.e., θ) or impede individuals' willingness or ability to start new businesses (i.e., β). While these factors are difficult to observe, the number and size of existing firms in the region arguably capture the opportunity constraints. That is, the level of entrepreneurial activity in the region is determined, in part, by the number of opportunities (arising from either the region's growth or knowledge investments) *not* exploited by existing firms (i.e., $1 - \theta$) (Audretsch et al., 2006). A greater number of existing firms suggests fewer opportunities left for individuals to exploit, but so does the presence of larger incumbent firms, given their presumably greater absorptive capacity.

> Hypothesis 4: The level of entrepreneurial activity in a given county *i* decreases with greater density of existing firms within the county.

> Hypothesis 5: The level of entrepreneurial activity in a given county *i* decreases as the average size of existing firms increases within the county.

As part of the fourth and final set of factors, the level of self-employment in the region as well as the level of education of the region's population may capture the willingness and/or ability of a region's workforce to engage in entrepreneurial activity in the region. In particular, higher levels of self-employment would seem to indicate a more supportive environment for entrepreneurial activity, since such self-employment implies the proclivity of the region's workforce to choose something other than wage-based employment. The population's educational attainment may capture the ability of would-be entrepreneurs to overcome any entrepreneurial barriers and/or assess the future profit potential of a given opportunity. Thus,

> Hypothesis 6: The level of entrepreneurial activity in a given county *i* increases with higher levels of self-employment within the county.

> Hypothesis 7: The level of entrepreneurial activity in a given county *i* increases with higher levels of educational attainment within the county.

In turn, since the spillover model in Equation 1 suggests that individuals choose to become entrepreneurs or accept wage-based work by comparing the earning potential of doing the former versus the latter, it follows that better wage opportunities will reduce the likelihood that someone will opt to start their own business. The stronger effect, however, may be observed with the loss of wage employment since the earned wage is necessarily zero. Thus, for unemployed members of the workforce, the opportunity cost of choosing entrepreneurship over wage employment is substantially lowered, if not nullified. In other words, the spillover model predicts a positive relationship between the region's unemployment rate and the level of entrepreneurial activity. Thus,

> Hypothesis 8: The level of entrepreneurial activity in a given county *i* increases with higher unemployment within the county.

Research Design

The hypotheses established in the previous section predict changes in a county's rates of entrepreneurial activity, given changes in the specified characteristics of that county. Thus, the hypotheses are tested using a panel dataset of repeated (i.e., time-series) observations of the relevant variables within each county in the continental United States. The panel data make it possible to report fixed effects regression estimates in which each coefficient captures the change in the dependent variable, given a unit change in the specific independent variable. Such longitudinal data are preferable to a purely cross-sectional dataset because both statistical power and inference are dramatically improved. That said, the repeated measures introduce a few complications to the analysis that limit both the length of the study period and the number of counties included in the analysis.

Data Collection

To begin, annual county-level business establishment birth and death (EBD) data covering every available year, nearly every industry, and every county in the 50 United States were obtained from the U.S. Census Bureau's Business Information Tracking Series (BITS) file. The EBD tabulations report single-unit, multi-unit, and total establishment births and deaths by four-digit SIC or five-digit NAICS code from 1990 to 2006 (Plummer & Headd, 2007). To facilitate data collection for the independent variables and the mapping of the locations of entrepreneurial activity, the EBD data are georeferenced to the 2000 Census county boundary definitions. Using the 2000 county definitions requires minor corrections to the data aggregations to accommodate changes in the Census Bureau's data collection from Virginia's independent cities and the redefined Miami-Dade County boundary in Florida. Using the 2000 boundaries omits Broomfield County in Colorado, which was created in 2001 from portions annexed from its four neighboring counties. As a result, the dataset includes 3,009 counties.[2]

Information for the independent variables originates from several public sources. The U.S. Census Bureau's 2000 Gazetteer file and County Business Patterns database are the sources, respectively, for county land areas and the number of existing establishments. The Bureau of Economic Analysis regional accounts provide the information on population growth, income growth, and proprietors' share of the labor force. The U.S. Patent and Trademark Office provides the number of patent grants per county and the Economic Research Service of the U.S.

[2] Alaska is omitted because of substantial changes in the composition of its counties and Hawaii is omitted because the spatial analysis methods used here require that the counties share a common border (i.e., the counties are not separated by water).

Department of Agriculture is the source of the college degree information. Finally, the Bureau of Labor Statistics Labor Local Area Unemployment Statistics (LAUS) file yields the labor force data for each county. Unfortunately, not all of the data used to calculate the independent variables are available for all 17 years of the EBD tabulations. The patent dataset used for the analysis, for example, is available for 1990 to 1999 only. Thus, all the maps showing the locations of entrepreneurial activity derive from data from the full 17-year period, while the regressions reported in Table 6 cover a shorter ten-year time period.

Measuring the Rate of New Firm Births

For this study, firm births are measured by the number of single-unit establishment births in the county. Since a single-unit establishment refers to the only physical location where a firm conducts its business or operations, a single-establishment birth is a reasonable proxy for the emergence of a new firm (Armington & Acs, 2002). In turn, the *rate of new firm births* in each county is calculated as the number of single-unit establishment births in year *t* divided by the number of workers (in thousands) in the labor force regardless of employment status in year *t-1*. This labor force method for calculating the rate of firm births, which is consistent with the Armington and Acs (2002) approach, facilitates comparisons of entrepreneurial activity across counties of varying sizes and captures the tendency of workers in the county to start new businesses (Audretsch & Fritsch, 1994).

Given the expectation that the geographic distribution of firm births varies by industry, the county rate of new firm births per worker is calculated for seven industry sectors based on a modification of the definitions used by Armington and Acs (2002) as shown in Table 1. The principal difference from Armington and Acs's (2002) study is the separation of high technology industries from the manufacturing sector based on Henderson's (2003) industry definition. The central complication with the industry classifications is that the EBD data are indexed by Standard Industrial Classification (SIC) codes from 1990 to 1998 and North American Industy Classification System (NAICS) codes from 1999 to 2006. Fortunately, the SIC and NAICS sector definitions correspond well enough to add only a little noise to the data. The exception is the business service industries for which the SIC and NAICS codes poorly correspond. As a result, the industry disaggregation yields *nine* calculations of each county's firm birth rates: the overall rate of firm births in all sectors; the new firm birth rates in the manufacturing, extractive, retail trade, local market, and high technology sectors; and the rate of firm births in business services from 1990 to 1999 and from 1999 to 2006.

Table 1: Industry Classifications

Sector (Description)	SIC Classification	NAICS Classification
Distributive (transportation, public utilities, wholesale trade)	4000-5199	48-49, 42
Manufacturing (excluding high technology)	2000-3999	31-33
Extractive (agricultural services and mining)	0700-1499	11, 21
Retail Trade	5200-5999	44-45
Local Market (construction, consumer, and financial services excluding business services)	1500-1799 6000-8999	23, 52-53
Business Services (1990-1998) (including engineering, accounting, research, and management services)	7300-7399 8700-8799	
Business Services (1999-2006)		54
High Technology (computers, electronic components, aircraft, and medical instruments)	357, 367, 372, 384	33411, 33331, 33441, 33422, 33431, 54171, 33641, 33911, 33451

Mapping the Location of New Firm Births

Three types of maps are created to indicate the location of new firm births and to test Hypothesis 1. The first type is the *percentile map*, which categorizes the counties' rates of new firm births into one of six percentile ranges (see Legend 1). Counties with new firm birth rates of less than 1 percent are shown in dark blue; those with increases of more than 99 percent are shown in red; four other percentile ranges between these poles are displayed in lighter shades of color.

The second map is a *circular cartogram* map that resizes each county according to its rate of new firm births—that is, the higher the rate of new firm births, the larger the area of the circle in the cartogram (see Legend 2). The circular cartograms make it possible to compare the rates of new firm births across counties without the county's size biasing the interpretation or comparison. In all of the circular cartograms, the nonoutlying observations are green, the upper outliers are shown in red, the lower outliers are blue, and zero observations are white or transparent. The outliers are observations with values well outside the interquartile range (the range between the top of the lower quartile and the bottom of the upper quartile).

The third type of map is a *LISA cluster map.* LISA or "local indicators of spatial association" maps indicate the presence or absence of significant spatial clusters or outliers for each location. These maps require the calculation of two statistics—the *global* and *local* Moran's I indicators for spatial autocorrelation. Calculating these statistics requires the construction of a spatial weights matrix, which specifies the spatial structure of the expected relationship across county boundaries (Plummer, 2010). In the present study, the spatial weights matrix (W) is a row-standardized "first-order, queen contiguity" matrix, meaning that each county's neighborhood set includes all its adjacent (i.e., tangent and border-sharing) counties. Row standardization means that the original binary matrix—in which each element equals one when two adjacent counties are neighbors and zero otherwise—is transformed so that each row of the matrix sums to one. Row standardization allows for the calculation of the spatial lag (Wy_j), which is the value of y averaged across the set of neighboring counties J.

Armed with the weights matrix, the global Moran's I tests for the simple linear relationship between the given variable (y_i) in county i and its spatial lag (Wy_j) (Anselin, 2001). A positive and statistically significant Moran's I statistic indicates that values of y are spatially dependent, thus providing support for Hypothesis 1 (the level of entrepreneurial activity in a given county is positively associated with the level in neighboring counties) (Anselin & Bera, 1998). Next, to identify the specific locations where the variable y is spatially correlated, the global Moran's I statistic is decomposed to calculate a LISA statistic for each county (Anselin, 1995; Anselin, Syabri, & Smirnov, 2002). As with the global indicator, a positive and statistically significant LISA means that the value of y observed in county i is similar to the spatially weighted average value of y in the set of neighboring counties J.

Using this information, the LISA cluster map indicates the locations where the statistically significant local Moran's I statistics are either positive or negative (Anselin et al., 2002). In fact, the LISA cluster map indicates the location of four types of spatial autocorrelation (see Legend 3). First, the “high-high” clusters—shown by the deep red color—are those counties with high values of *y* surrounded by counties with similarly high values of *y*. Second, the “low-low” clusters—indicated by the deep blue color—are those counties with low values of *y* surrounded by counties with similarly low values of *y*. These high-high and low-low clusters indicate positive spatial autocorrelation. Third, the “low-high” clusters—indicated by the light blue color—are those counties with low values of *y* surrounded by counties with high values of *y*. Finally, the “high-low” clusters—indicated by the light red color—are those counties with high values of *y* surrounded by counties with low values of *y*. These last two types of clusters are called spatial outliers and indicate negative spatial autocorrelation.

In projecting the three sets of maps, the rates of new firm births are altered slightly to facilitate the spatial analysis. First, because only the cross-sectional spatial correlation is of interest in testing Hypothesis 1, the 16-year average of the new firm birth rate for each sector is mapped. Second, these average rates are “smoothed” to address the variance instability created by the denominator in the rate calculation (Anselin, Syabri, & Kho, 2006). Without the rate smoothing, the birth rates in counties with extremely small labor forces will be spurious outliers making any comparison of the raw rates misleading. Thus, the rates shown in the maps are stabilized by the Empirical Bayes (EB) smoother, which essentially “pulls” the outlier rates towards the overall mean with the rates from the counties with smaller workforces undergoing more shrinkage than counties with larger workforces.

Calculation of the Independent Variables

Given the hypotheses established in the previous section, eight independent variables are defined for each county. To test Hypothesis 2, economic growth is captured by *income growth,* which is the annual change in per capita income from year *t-1* to *t* divided by per capita income in year *t-1*. Since the county’s economy also grows with the number of consumers, economic growth is also measured by *population growth,* which is the annual change in population from year *t-1* to *t* divided by total population in year *t-1*. To test Hypothesis 3, *knowledge* is the number of patent grants in year *t* divided by the number of business establishments in year *t*. As mentioned, the patent data are available from 1990 to 1999 only, which limits the study period for the regression analysis to this 11-year time period.

To test Hypotheses 4 and 5 regarding the influence of the county’s opportunity constraints, *density* is the number of business establishments in year *t* per county square mile and *establishment size* is the number of employed workers in the county in year *t* divided by the number of existing business establishments also in year *t*. To test Hypotheses 6 and 7 regarding the willingness and ability of the region’s workforce to engage in start-up activity, the county’s level of self-employment is measured by the *share of proprietors,* which is the number of business sole proprietors and partners in year *t* divided by the total labor force in year *t*. In turn, *college degree* is the percentage of adults older than 25 years of age holding at least a college degree. Because the college degree variable is available for 1990 and 2000 only, the observations for the intervening years are derived via linear interpolation. Finally, to test Hypothesis 8, the *unemployment rate* is the number of unemployed workers in year *t* divided by the total labor force in year *t*.

Model Specification and Estimation

The regression model for testing Hypotheses 2 through 8 derives from the usual fixed effects (within subjects) model specification,

$$y_{ist} = X_{it}\beta + \mu_i + \varepsilon_{it} \tag{2}$$

where y_{it} is the rate of new firm births in sector *s* at time *t*, X_{it} is a matrix of the independent variables, β is a vector of coefficients to be estimated, μ_i is panel-specific error term representing the unobserved effects peculiar to each county *i*, and ε_{it} is the random error term. This specification controls for the effect of any unobserved variables specific to each county that are constant over time. Moreover, the coefficients are interpreted as the "internal response" of the dependent variable in the county to changes in the independent variables within the county.

To account for the effect of outliers and to estimate the β coefficients as elasticities (i.e., the percentage change in the dependent variable given a 1 percent change in the independent variable), the model given by Equation 2 is transformed into log-linear form. That is, with the exception of the income growth and population growth variables, given their negative values, the variables in X_{it} and y_{it} are transformed by the natural log. For all the dependent variables, as well as the knowledge variable—which included observations with zero values—the natural log transformation required the use of a started log. Thus, a small constant equal to one divided by the number of workers in the labor force was added to each observation before taking its natural log. As a result, the results reported in Table 6 are estimates of the following model,

$$ln(y_{ist}) = \alpha + \beta_1 ln(\text{Establishment Size})_{it} + \beta_2(\text{Income Growth})_{it} + \beta_3(\text{Population Growth})_{it} + \beta_4 ln(\text{Share of Proprietors})_{it} + \beta_5 ln(\text{Density})_{it} + \beta_6 ln(\text{Knowledge})_{it} + \beta_7 ln(\text{Unemployment Rate})_{it} + \beta_8 ln(\text{College Degree})_{it} + \mu_i + \varepsilon_{it} \tag{3}$$

Estimating Equation 3 using the standard fixed effects estimator requires the assumption that the errors are uncorrelated within and across panels and homoskedastic. Of course, given the expectation that the county rates of new firms will exhibit spatial autocorrelation, the usual assumptions of the fixed effects model are likely to be violated. As a result, Equation 3 is estimated using the Driscoll-Kraay (Driscoll & Kraay, 1998; Hoechle, 2007) estimator that produces heteroskedastic and autocorrelation consistent estimates robust to general forms of spatial and temporal correlation. As a result, the covariance estimates account for any spatial autocorrelation across counties, any temporal autocorrelation within counties from year to year, and any violation of the homoskedasticity assumption (Driscoll & Kraay, 1998). Unlike other available panel estimators, the Driscoll-Kraay estimator is feasible even when, as in this case, the number of panels (N) is larger than the number of time periods (T).

The Driscoll-Kraay estimator is not without its limitations and it is reasonable to ensure that its use is justifiable. Thus, following the guidance of Hoechle (2007), three diagnostic procedures are completed to validate the results of the Driscoll-Kraay estimator. First, in addition to the Moran's I tests used to create the LISA cluster maps, a diagnostic test for cross-sectional spatial correlation in Equation 3 is applied to the standard fixed effects estimates to ensure that the Driscoll-Kraay estimator is justified. Pesaran's cross-sectional dependence (CD) statistics tests the null that the residuals in Equation 3 are uncorrelated across counties. Second, diagnostic tests of the nulls of homoskedastic and serially uncorrelated residuals are applied to the standard fixed effects estimates. Finally, a modified Hausman test for fixed effects robust to general forms of spatial and temporal correlation is applied to the Driscoll-Kraay estimates.

Results

Summary information is reported in Table 2. The table indicates that across all sectors there are nearly five single-unit establishment births per 1,000 workers during the study period within a range of zero and 28.49 births per 1,000 workers. Only 55 of the 3,009 counties in the dataset show zero single-establishment births in all sectors at least once during the study period. The table also summarizes the rates of new firm births in the seven industrial sectors. Given the dominance of retail trade in the U.S. economy, it is not surprising that this industry sector has the highest rate of new firm births (1.06 births per 1,000 workers), followed closely by the local market industries (1.03 births per 1,000 workers). By far the lowest rate of new firm births is in the high technology sector (0.01 births per 1,000 workers). This suggests, perhaps correctly, that new firms are rare in this sector, but it is also possible that the large difference relative to, say, the manufacturing sector is a function of the industry aggregations shown in Table 1.

The bottom of Table 2 summarizes the independent variables, which are within the expected ranges with two exceptions. First, somewhat surprisingly, given that the majority of the nation's 6 to 7 million business establishments have fewer than four employees, the average establishment size in the observed counties is a little more than 22 workers per place of business, within a range of 6.2 and 202.5 workers per place of business. A review of the variable, however, indicates the value is "real" in that is not the result of a miscalculation. Second, while the mean share of proprietors is consistent with the mean reported by Armington and Acs (2002), the maximum number of proprietors per worker in the labor force is greater than one. This probably reflects key differences in how the Bureau of Economic Analysis (BEA) counts the number of proprietors (the numerator) and the Bureau of Labor Statistics (BLS) counts the number of workers (the denominator).[3] Since the bias in the share of proprietors is small and constant across counties, the variable is unchanged prior to entering the regression model.

[3] The BEA count of proprietors includes the *total* number of full-time and part-time sole proprietors and individual business partners. The BLS labor force measure, on the other hand, is the *average annual* number of employed workers and unemployed workers including those people working in their own business. More importantly, unemployed persons are those workers available for work and making "specific efforts" to find employment during the four-week reference period. It seems likely that the BEA measure slightly overstates the number of proprietors, while the BLS measure slightly understates the size of the labor force.

Tables 3 and 4 shed additional light on the comparative levels of entrepreneurial activity in U.S. counties. In particular, Table 3 is a list of the top 20 counties ranked by the total number of single-unit establishment births by given sector. In raw counts, it is clear that Los Angeles,

Table 2: Descriptive Statistics

Variables	Mean	Std. Dev.	Min	Max
Single-Establishment Births per 1,000 Workers				
All Sectors	4.71	2.05	0	28.49
Manufacturing	0.24	0.26	0	5.41
Retail Trade	1.06	0.69	0	14.99
Local Market	1.03	0.72	0	11.48
High Tech	0.01	0.03	0	2.16
Extractive	0.15	0.22	0	3.80
Business Services (1990-1998)	0.37	0.36	0	5.16
Business Services (1999-2006)	0.32	0.34	0	5.86
Distributive	0.50	0.39	0	7.52
Independent Variables				
Establishment Size	22.69	7.82	6.23	202.50
Per Capita Income Growth	0.04	0.05	-0.41	0.84
Population Growth	0.01	0.02	-0.28	0.36
Share of Proprietors	0.26	0.12	0.06	1.48
Agglomeration Density	6.54	81.39	0.00	4601.60
Knowledge (per 1,000 workers)*	0.23	0.40	0	7.06
College Degree	15.22	7.39	3.84	59.83
Unemployment Rate	6.06	3.21	0.90	39.60

* Per 1,000 workers for this table only. Knowledge = patents per worker in all other tables.

Cook (Chicago), and New York counties are three regions with considerable levels of entrepreneurial activity. In fact, Los Angeles loses its top ranking only to Santa Clara County and Harris County (TX) in the high technology and extractive sectors, respectively. The rankings in Table 3 are consistent with the knowledge spillover model since it follows that communities with more people should have higher absolute levels of entrepreneurial activity. Of course, this means little comparatively, since such raw counts fail to capture the average tendency of the community's residents to become entrepreneurs.

With this in mind, Table 4 shows the top 20 counties ranked by the rate of firms births per 1,000 workers by sector. These rankings are qualitatively different from those in Table 3, in that most large metropolitan areas are absent. Table 4 suggests that the nation's interior and northwestern counties—especially in Colorado, Utah, and Washington states—have the highest

Table 3: County Rankings by Sector, Total Single-Establishment Births

Rank	All Sectors	Local Market Industries	Retail Trade Industries	Manufacturing Industries	High Tech Industries
1	Los Angeles, CA	Los Angeles, CA	Los Angeles, CA	Los Angeles, CA	Santa Clara, CA
2	Cook, IL	Cook, IL	Cook, IL	New York, NY	Los Angeles, CA
3	New York, NY	Maricopa, AZ	New York, NY	Orange, CA	Orange, CA
4	Dade, FL	Orange, CA	Dade, FL	Cook, IL	San Diego, CA
5	Orange, CA	San Diego, CA	Harris, TX	Harris, TX	Middlesex, MA
6	Harris, TX	Dade, FL	Orange, CA	San Diego	Maricopa
7	Maricopa, AZ	Harris, TX	Maricopa, AZ	Maricopa, AZ	Alameda, CA
8	San Diego, CA	New York, NY	San Diego, CA	Dade, FL	King, WA
9	Broward, FL	King, WA	Kings, NY	Santa Clara, CA	Cook, IL
10	Dallas, TX	Broward, FL	Broward, FL	Dallas, TX	Harris, TX
11	King, WA	Dallas, TX	Queens, NY	King, WA	Dallas, TX
12	Nassau, NY, NY	Palm Beach, FL	Dallas, TX	Kings, NY	Dade, FL
13	Palm Beach, FL	Suffolk, NY	King, WA	Broward, FL	Hennepin, MN
14	Santa Clara, CA	Nassau, NY	Nassau, NY	Queens, NY	Broward, FL
15	Kings, NY	Clark, NV	Suffolk, NY	Alameda, CA	San Mateo, CA
16	Queens, NY	Queens, NY	Palm Beach, FL	San Bernardino, CA	Salt Lake, UT
17	Suffolk, NY	Riverside, CA	Wayne, MI	Hennepin, MN	Montgomery, MD
18	Clark, NV	Salt Lake, UT	Santa Clara, CA	Suffolk, NY	Boulder, CO
19	Oakland, MI	Santa Clara, CA	Oakland, MI	Tarrant, TX	New York, NY
20	Hennepin, MN	Kings, NY	Clark, NV	Oakland, MI	Travis, TX

Rank	Extractive Industries	Distributive Industries	Business Services (1990-1998)	Business Services (1999-2006)
1	Harris, TX	Los Angeles, CA	Los Angeles, CA	Los Angeles, CA
2	Los Angeles, CA	New York, NY	Cook, IL	Cook, IL
3	Dallas, TX	Dade, FL	New York, NY	New York, NY
4	Maricopa, AZ	Cook, IL	Harris, TX	Orange, CA
5	King, WA	Harris, TX	Orange, CA	Dade, FL
6	San Diego, CA	Orange, CA	Maricopa, AZ	Maricopa, AZ
7	Palm Beach, FL	Broward, FL	Dallas, TX	San Diego, CA
8	Oklahoma, OK	Maricopa, AZ	Dade, FL	Harris, TX
9	Suffolk, NY	San Diego, CA	San Diego, CA	Broward, FL
10	Cook, IL	Dallas, TX	Broward, FL	Santa Clara, CA
11	Orange, CA	Queens, NY	King, WA	King, WA
12	Broward, FL	Kings, NY	Santa Clara, CA	Dallas, TX
13	Tarrant, TX	King, WA	Hennepin, MN	Palm Beach, FL
14	Midland, TX	Nassau, NY	Middlesex, MA	Fairfax, VA
15	Riverside, CA	Bergen, NJ	Nassau, NY	Fulton, GA
16	Tulsa, OK	Suffolk, NY	Fairfax, VA	Nassau, NY
17	Nassau, NY	Palm Beach, FL	Palm Beach, FL	Clark, NV
18	Oakland, MI	Santa Clara, CA	Oakland, MI	Hennepin, MN
19	Dade, FL	Hennepin, MN	Fulton, GA	Middlesex, MA
20	Clark, NV	Alameda, CA	Du Page, IL	Oakland, MI

levels of entrepreneurial activity per person during the study period. This is consistent with the knowledge spillover model, given the population growth in these western states over the last two

Table 4: County Rankings by Sector, Total Single-Establishment Births per Worker

Rank	All Sectors	Local Market Industries	Retail Trade Industries	Manufacturing Industries	High Tech Industries
1	San Juan, CO	San Miguel, CO	San Juan, CO	Sanders, MT	Golden Valley, MT
2	Ouray, CO	Valley, ID	Ouray, CO	Carter, MO	Harding, NM
3	San Miguel, CO	Eagle, CO	Mineral, CO	Benewah, ID	Los Alamos, NM
4	Pitkin, CO	Summit, CO	Hinsdale, CO	Reynolds, MO	Santa Clara, CA
5	Summit, CO	Archuleta, CO	Archuleta, CO	Webster, WV	Custer, ID
6	Teton, WY	Teton, ID	Summit, CO	Bradley, AR	Boulder, CO
7	Archuleta, CO	San Juan, WA	Grand, CO	Forest, WI	San Juan, CO
8	Eagle, CO	Ouray, CO	San Miguel, CO	San Juan, CO	Archuleta, CO
9	Valley, ID	Pitkin, CO	Pitkin, CO	Wallowa, OR	Jefferson, IA
10	San Juan, WA	Blaine, ID	Nantucket, MA	Montgomery, AR	Carson City, NV
11	Grand, CO	Grand, CO	Lincoln, NM	Meagher, MT	Griggs, ND
12	Summit, UT	Routt, CO	Fredericksb'g, VA	Granite, MT	Motley, TX
13	Gunnison, CO	Gunnison, CO	Dukes, MA	Ripley, MO	Douglas, NV
14	Blaine, ID	Teton, WY	Gunnison, CO	Mineral, MT	Charlottesville, VA
15	Routt, CO	Alpine, CA	Emporia, VA	Clearwater, ID	Kane, UT
16	Sublette, WY	Summit, UT	Valley, ID	Winn, LA	Gallatin, MT
17	Fredericksb'g, VA	Mineral, CO	San Juan, WA	Adams, ID	Deschutes, OR
18	Mineral, CO	Washington, UT	Teton, WY	Boundary, ID	Fairfax City, VA
19	Teton, ID	Garfield, CO	Keweenaw, MI	Lincoln, MT	Skamania, WA
20	Hinsdale, CO	Nantucket, MA	Blaine, ID	Bonner, ID	Clay, KS

Rank	Extractive Industries	Distributive Industries	Business Services (1990-1998)	Business Services (1999-2006)
1	Shackelford, TX	Santa Cruz, AZ	Fairfax City, VA	Fairfax City, VA
2	Kodiak Island, AK	Webb, TX	San Miguel, CO	Pitkin, CO
3	Russell, KS	Maverick, TX	Pitkin, CO	Falls Church, VA
4	Sublette, WY	Magoffin, KY	Summit, CO	Carson City, NV
5	Ness, KS	Buchanan, VA	Carson City, NV	New York, NY
6	Sitka, AK	Thomas, NE	Falls Church, VA	Jefferson, IA
7	Throckmorton, TX	Valdez-Cord., AK	Teton, WY	Teton, WY
8	Young, TX	Lake & Pen., AK	New York, NY	Summit, UT
9	Duchesne, UT	New York, NY	Summit, UT	Boulder, CO
10	Barber, KS	Bristol Bay, AK	Jefferson, IA	Eagle, CO
11	Ochiltree, TX	Wichita, KS	Eagle, CO	Fredericksb'g, VA
12	McDowell, WV	Mingo, WV	Ouray, CO	Summit, CO
13	Reagan, TX	Atchison, MO	San Juan, WA	Ouray, CO
14	Wrang.-Peter., AK	Ellis, OK	Boulder, CO	Fulton, GA
15	Valdez-Cord., AK	Lane, KS	Charlottesville, VA	San Miguel, CO
16	Johnson, WY	Kingsbury, SD	Fulton, GA	Loudoun, VA
17	Uintah, UT	Boundary, ID	Fredericksb'g, VA	Gallatin, MT
18	Stephens, TX	Webster, WV	Douglas, CO	Manassas C'y. VA
19	Midland, TX	Jackson, CO	Collier, FL	Sublette, WY
20	Kingfisher, TX	Letcher, KY	Blaine, ID	Charlottesville,VA

decades. Colorado's population, for example, grew nearly 44 percent from 1990 (3.3 million people) to 2006 (4.75 million people).

Where in America?

Figures 1 through 27 show the location of entrepreneurial activity in the continental United States. Figures 1 through 9 are the percentile maps showing the distributions of the overall and sector-specific rates of new firms in six percentile ranges. Figures 10 through 18 are the circular cartograms in which the area of the county's circle reflects the value of the firm birth rate, the red circles are the upper outliers, and the blue circles are the lower outliers. Finally, Figures 19 to 27 are the LISA cluster maps based on the global and local Moran's I test for spatial autocorrelation. Indeed, each LISA cluster map reports the global Moran's I statistic and its statistical significance. The Moran's I estimates—all significant at the 1 percent level—range from a low of 0.14 for the high technology industries to a high of 0.47 for the local market sector. This indicates that, regardless of industry, the level of entrepreneurial activity in a given county is positively related to the level of entrepreneurial activity in its neighboring counties. Thus, Hypothesis 1 is supported.

Although these three sets of maps illustrate the location of entrepreneurial activity in the continental United States, they reveal different dimensions of this activity. In other words, each type of map has its unique interpretation. As an example, Figure 1 is the percentile map for the new firm birth rate in all sectors. Counties from light to dark blue are those in the three percentiles below the median value of the firm birth rate and counties colored yellow, orange, and red are those in the three percentiles above the median. Figure 1 clearly shows the highest rate of new firm births are in parts of New Mexico, Colorado, Wyoming, and Idaho. Interestingly, pockets of Maine, New Hampshire, Florida, and Michigan show rates of new firm births in the 90^{th} to 99^{th} percentile range. In contrast, a large area of counties with low rates of new firm births stretches from New York and Pennsylvania to the east to Illinois and Wisconsin to the west.

In turn, Figure 10 is the corresponding circular cartogram of the new firm birth rate for all sectors. The map shows a number of upper outliers in the western states, including the areas in the upper percentile ranges shown in Figure 1. Figure 10 also shows outliers in several Northwest and Midwest states, down the eastern seaboard, and Texas. One lower outlier appears as a small dark blue circle in the state of Georgia. This lower outlier is Echols County, which added only 22 new firms from 1990 to 2006, making for an average new firm birth rate of 0.09 new firms per 1,000 workers. Consistent with Figure 1, the circular cartogram in Figure 10 indicates the highest rates of new firm births (i.e., the largest circles) in portions of Colorado and Wyoming. One interesting result from the circular cartogram in Figure 10 is New York County's identification as an outlier, while the two counties with which it shares top rankings in Table 3—Los Angeles and Cook Counties—are not.

Finally, Figure 19 is the corresponding LISA cluster map of the rate of new firm births across all sectors. The dark red counties in the cluster map are those with high levels of entrepreneurial activity bordered by counties with similarly high levels of entrepreneurial activity. High-high clusters of entrepreneurial activity are evident around the District of Columbia, Florida, Missouri, central Texas, Oregon, Washington, Georgia, and the northern tip of Michigan's lower peninsula. The largest and most conspicuous high-high cluster of entrepreneurial activity extends from Arizona and New Mexico to the south, through Colorado and eastern Utah, and into Idaho and Montana. In contrast, the dark blue counties show an extensive low-low cluster in the states that constitute the industrial "Rust Belt" from New York through Ohio. In turn, the pink shaded counties are "oases" of entrepreneurial activity. These pink-shaded high-low areas appear in the Texas Panhandle, Ohio, Pennsylvania, and North Carolina. Similarly, the counties shaded light blue—including Miami-Dade County and Prince Georges County in Maryland—indicate "low-high" clusters where the given county seems unable to match the level of entrepreneurial activity in its neighboring counties.

In the case of the high technology industries, the percentile map in Figure 5 shows, interestingly enough, Santa Clara County at the heart of Silicon Valley and the counties of Boston's Route 128 in the top percentile. Joining this group are Boulder County in Colorado as well as counties in Idaho, Montana, Texas, and other parts of California. The circular cartogram in Figure 14 yields a similar interpretation, but shows Golden Valley County in Montana with a high rate of high technology new firm births followed by Santa Clara County in California. Correspondingly, the LISA cluster map in Figure 23 clearly shows high-high clusters of high-tech start-ups around Boston, the San Francisco Bay Area, and the Raleigh-Durham area of North Carolina, which is consistent with the conventional view of these regions as exemplars of high technology clusters. That said, the LISA cluster map also shows high-high clusters of high technology entrepreneurial activity is other regions of the United States including Boulder and Denver in Colorado, Minneapolis-St. Paul in Minnesota, the District of Columbia, Florida's "Space Coast," and large portions of the Pacific Northwest. In addition, the cluster map shows that Centre County in Pennsylvania is one of many oases of high technology entrepreneurial activity, no doubt due to the presence of Pennsylvania State University.

Why in America?

Table 5 reports the correlations of the variables and Table 6 reports the results of the regression estimates. As noted earlier, the patent data to calculate the knowledge variable are available only for 1990 to 1999. This makes it impossible to estimate a model with the rate of firm births in the business services sector from 1999 to 2006. Thus, the business services firm birth rate is for 1990 to 1998 only.

Table 5 indicates that the firm birth rates in the retail trade, business services, and local market sectors are highly correlated with each other and with the overall firm birth rate. This result aside, all other correlations of firm birth rates across sectors are minimal. This may imply that the business services, retail trade, and local market birth rates are driven by similar county characteristics. Among the independent variables, the correlations are minimal. That said, the relatively high correlation between college degree and knowledge fits with the premise that new knowledge is created by people with higher levels of educational attainment. Moreover, the relatively strong negative correlation between the unemployment rate and college degree suggests that the chances of being unemployed are lower where people have higher levels of educational attainment.

Table 6 reports the regression estimates of Equation 3. In all cases, the statistical diagnostics validate the use of the Driscoll-Kraay fixed effects estimator. As mentioned, the estimates are limited to the first 10 years of the study period (i.e., 1990 to 1999) except in the case of the business services sector estimates, which are limited to 1990 to 1998 by the period of the rate calculation. This explains the difference in the number of observations and groups across the eight model estimates. The r-squared estimates range between 0.30 and 0.69 and the F-statistics are significant at the 1 percent level. The very high F-statistic for the high technology sector estimates is troublesome given that only four of the nine coefficient estimates are statistically significant. This may indicate the influence of multicollinearity and suggests the results for this model should be accepted cautiously.[4]

[4] Multicollinearity exists when two or more predictor variables in a multiple regression model are highly correlated.

Table 5: Correlations

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	All Sectors	1														
2	Manufacturing	0.33	1													
3	Retail Trade	0.71	0.16	1												
4	Local Market	0.76	0.15	0.39	1											
5	High Tech	0.09	0.13	0.01	0.07	1										
6	Extractive	0.32	0.03	0.16	0.15	-0.01	1									
7	Business Services	0.53	0.06	0.19	0.44	0.10	0.10	1								
8	Distributive	0.39	0.13	0.16	0.15	0.03	0.11	0.10	1							
9	Establishment Size	-0.53	-0.13	-0.38	-0.34	-0.03	-0.20	-0.28	-0.24	1						
10	Per Capita Income Growth	0.01	0.01	0.00	0.01	-0.01	0.00	0.01	0.02	0.00	1					
11	Population Growth	0.24	0.08	0.09	0.33	0.04	-0.01	0.28	0.00	0.15	-0.10	1				
12	Share of Proprietors	0.26	0.05	0.28	0.13	0.00	0.19	-0.12	0.18	-0.25	0.00	-0.21	1			
13	Agglomeration Density	0.07	0.03	0.02	0.02	0.01	-0.03	0.16	0.06	-0.05	0.00	-0.01	-0.05	1		
14	Knowledge	0.02	-0.02	-0.08	0.07	0.06	-0.01	0.25	-0.04	-0.05	0.02	0.08	-0.11	0.05	1	
15	College Degree	0.32	-0.04	0.09	0.33	0.09	0.05	0.60	0.00	-0.26	0.01	0.18	-0.13	0.16	0.41	1
16	Unemployment Rate	-0.03	0.13	0.05	-0.08	-0.02	-0.03	-0.14	0.00	0.09	-0.03	-0.01	-0.04	0.00	-0.16	-0.34

Table 6: Log-Linear Fixed Effects Regression Analysis

Determinants of New Firm Birth Rates (ln) by Sector

Variables	1 All	2 Man.	3 Ret.	4 Loc.	5 High	6 Ext.	7 Bus.	8 Dis.
Establishment Size (ln)	-1.32 **	-1.43 **	-1.60 **	-1.09 **	0.02	-0.73 **	-0.76 **	-1.65 **
	[-25.10]	[-9.36]	[-10.12]	[-9.23]	[0.18]	[-2.92]	[-5.18]	[-7.56]
Income Growth	0.16 **	0.41	0.44	0.08	-0.25	1.10	0.06	0.60 *
	[2.38]	[1.58]	[1.60]	[0.51]	[-1.42]	[1.31]	[0.36]	[1.71]
Population Growth	2.22 **	3.25 *	4.41 *	2.29 **	-1.32 *	6.90 **	1.48 **	3.34 **
	[4.80]	[2.31]	[1.96]	[4.06]	[-1.92]	[3.09]	[2.74]	[2.51]
Share of Proprietors (ln)	-0.23 **	-0.56 **	-0.47 **	0.04	-0.04	0.05	0.30 **	-0.17 *
	[-6.53]	[-8.04]	[-4.22]	[0.53]	[-0.66]	[0.41]	[3.79]	[-2.25]
Density (ln)	0.40 **	0.35 *	0.29	0.69 **	-0.06	-0.51	1.22 **	0.54 *
	[5.96]	[2.04]	[1.07]	[16.95]	[-0.15]	[-0.59]	[6.79]	[2.20]
Knowledge (ln)	-0.08 **	-0.06	-0.28 **	-0.19 **	0.56 *	-1.11 **	-0.10 *	-0.30 **
	[-5.36]	[-1.45]	[-5.15]	[-4.33]	[1.96]	[-2.41]	[-2.30]	[-5.22]
Unemployment Rate (ln)	0.08 **	0.31 **	0.24 **	0.05	-0.20	0.52	-0.16 **	0.17 *
	[4.76]	[3.00]	[2.35]	[1.25]	[-1.62]	[1.63]	[-4.66]	[2.27]
College Degree (ln)	-0.44 **	-1.36 **	-1.93 **	-0.18	0.33 **	-1.27	0.40 *	-0.59
	[-3.43]	[-5.32]	[-2.46]	[-0.80]	[2.84]	[-1.63]	[2.20]	[-1.36]
Constant	5.72 **	4.07 **	6.94 **	2.36 **	-2.95 *	-5.10 **	-0.31	3.10 **
	[13.94]	[5.35]	[4.38]	[2.71]	[-1.97]	[-4.03]	[-0.30]	[3.22]
Observations	22783	22783	22783	22783	22783	22783	20331	22783
Number of groups	3009	3009	3009	3009	3009	3009	2985	3009
R-squared	0.69	0.38	0.36	0.45	0.48	0.30	0.49	0.53
F-Statistic	2837	162.2	1813	596.1	3565	144.5	336.7	5665

The income growth and population growth coefficients are tests of Hypothesis 2 (entrepreneurial activity increases with economic growth). As shown in Table 6, the coefficient estimate for income growth is positive and statistically significant in only two of the eight models. In the overall estimates, the estimated coefficient in Model 1 suggests that the rate of new firm births across all sectors increases 2 percent when the per capita income growth increases by one-tenth of a unit (i.e., from 0.1 to 0.2 or from 0.8 to 0.9). Similarly, the coefficient estimate in Model 8 suggests that a similar increase in per capita incomes corresponds to a 6 percent increase in the firm birth rate in the distributive sector. In contrast, the coefficient for population growth is statistically significant in all eight models and positive, except in Model 5. For the high technology sector, a tenth of a unit increase in population growth is associated with a 12 percent *drop* in that sector's rate of firm births. By comparison, the results indicate that a 0.10 increase in population growth corresponds to a 16 percent increase in business services birth rate and a 99 percent increase in the birth rate in extractive industries. In sum, the population growth estimates support Hypothesis 2 more strongly than do the estimates for income growth.

At odds with the prediction of Hypothesis 3, the knowledge coefficient estimates are *negatively* related to the rate of firm births except in the case of the high technology sector. In Model 1, for example, a 10 percent increase in the number of patents per worker in the county is associated with a 1 percent decrease in the firm birth rate across all sectors. An equal increase in knowledge also corresponds to a 1 percent drop in the business services birth rate and a 10 percent drop in the extractive sector birth rate. In the high technology sector, however, a 10 percent increase in the number of patents per worker is associated with a 5 percent increase in the sector's new firm birth rate. As stated, the negative coefficient estimates for knowledge yield no support for Hypothesis 3 concerning the relationship between a county's stock of knowledge and its rate of new firm formation. On the other hand, as will be discussed below, this finding does fit with a central assumption of the knowledge spillover model that new knowledge and economic growth stimulate quite different types of entrepreneurial opportunities.

For Hypotheses 4 and 5, density and establishment size capture the opportunity constraints in the knowledge spillover models. In particular, the pool of opportunities available to would-be entrepreneurs to exploit is smaller if the region is home to a higher proportion of (large) incumbent businesses. The significant estimates for density, however, are positive; Model 1, for example, indicates a 4 percent increase in the overall firm birth rate from a 10 percent increase in the number of existing establishments per square mile. The largest effect is in the business services sector, where a 10 percent increase in density corresponds to a 12 percent increase in the sector's rate of firm births. In contrast, establishment size is negative in seven of the eight models. Indeed, Model 1 indicates that a 10 percent increase in average size of existing establishments corresponds to a 12 percent reduction in the overall rate of new firm births. The largest effect is seen in the distributive sector, where a 15 percent decrease in the birth rate corresponds to a 10 percent increase in establishment size. These results strongly support Hypothesis 5 (entrepreneurial activity decreases with increasing average firm size), but yield no support for Hypothesis 4 (entrepreneurial activity decreases with density of existing firms).

Hypotheses 6 and 7 concern the willingness and ability of workers in a county to engage in entrepreneurial activity. Indeed, the share of proprietors is used as an indicator of the county's level of self-employment and its coefficient estimates are predicted to be positive. However, in all but one case, the significant coefficient estimate for this variable is negative. The exception is the business services sector where a 10 percent increase in the share of proprietors is associated with a 3 percent increase in the sector's firm birth rate. In turn, college degree as an indicator of educational attainment is also predicted to be positively related to the rate of new firm births. Instead, the coefficients for this variable are negative in three of the five statistically significant estimates. The two exceptions are the high technology and business services sectors where a 10 percent increase in the college degree is associated with a 3 percent and 4 percent increase in the respective sector birth rates. Thus, the support for Hypotheses 6 (entrepreneurial activity increases with self-employment) and 7 (entrepreneurial activity increases with educational attainment) is mixed.

Finally, the county's unemployment rate is meant to capture the relationship between entrepreneurial activity and the earning potential of working for an existing firm. Hypothesis 8 states that the relationship will be negative because poor wage opportunities should increase the likelihood that people will start new businesses. In Model 1, the coefficient estimate is negative and significant and suggests a 1 percent increase in the overall firm birth rate with a 10 percent increase in the county rate of unemployment. In the business services sector, however, the relationship is positive in that an equal decrease in the unemployment rate is associated with a 1 percent decrease in the sector's firm birth rate. In general, these results provide support for Hypothesis 8, but the negative relationship in the distributive sector is intriguing and worthy of discussion.

Discussion

The findings of this study are intriguing on a number of levels with implications for practitioners, policymakers, and researchers. First, the clearest support for any of the hypotheses is for the first: the spatial analysis clearly indicates that entrepreneurial activity concentrates geographically. Indeed, perhaps the most conspicuous observation is the entrepreneurial lows of the nation's Rust Belt states and the entrepreneurial highs of the Rocky Mountain regions during the 17-year period of the study (see Figure 19). A pivotal determinant for this pattern appears to be changes in county population. Indeed, the distribution of economic activity in Figure 19 corresponds to changes in county populations during a period in which many Rust Belt county populations shrank and many western state county populations grew (Perry & Mackun, 2001).

Second, the findings in this study indicate that the entrepreneurial activity in the high technology sector is a special case. As shown in Table 6, the sector proved the exception in the relationship new firm birth rates have to changes in population, the creation of new knowledge, and the educational attainment of the county population. The results in Figure 23 indicate that the fascination of scholars and policymakers with places like Silicon Valley, Boston's Route 128, and North Carolina's Research Triangle is deserved. Perhaps more interestingly, much the same may be said for the business services sector. The high correlation between the firm birth rates in these sectors and the evidence that both rely on an educated workforce imply a close link. In other words, it may be that the formation of new business services firms occurs partly as a response to high technology entrepreneurial activity.

Insights for Policy

The ramifications of this study's findings are particularly relevant for economic development authorities, which increasingly favor supporting local entrepreneurship over "smokestack chasing" (Quello & Toft, 2006). Indeed, several broad recommendations are implied from the findings. First, counties with access to an educated workforce and a local research and development (R&D) infrastructure favor entrepreneurial activity in no other sector than high technology. This may explain why the community around Penn State University in Centre County in Pennsylvania is an oasis of high technology entrepreneurial activity. It may also explain why some regions even with top research universities still find it difficult to encourage high technology start-up activity. The experience of South Carolina's Upstate Alliance may be a case in point. Although home to a top public research university and the center of a vibrant automotive cluster, the area's comparatively low levels of educational attainment may explain the struggle to attract and encourage entrepreneurial activity in targeted segments.[5]

Second, the findings suggest that one aspect of the SC Upstate Alliance's strategy is quite correct. The broad swaths of dark red and dark blue on the LISA cluster maps suggest that the spatial scale of the entrepreneurship process is larger than the land area of the average county. In other words, the level of entrepreneurial activity in one county seems to reinforce the level in nearby counties. According to the LISA cluster maps, it is rare for counties—those shown in pink—to achieve high levels of entrepreneurial activity when surrounded by counties with low levels of such activity. Therefore, aligning the goals and actions of a group of neighboring counties may be a necessary condition for encouraging entrepreneurial activity in any given region. In fact, the results suggest that the formation of county-level development alliances should ignore arbitrary boundaries, such as state borders, to avoid excluding counties crucial to the success of any shared development program.

Insights for Practice

Although the analysis is at the county level, the findings here suggest a number of factors entrepreneurs might consider in choosing a location for their new ventures. To be clear, the analysis is silent on the post-start-up ramifications of the location decision in that neither the prospects for survival nor the potential for growth is explored. This study only assesses the extent to which counties are supportive of new venture creation. Therefore, the results in Table 6

[5] The Upstate Alliance is an economic development initiative for the ten-county upstate region of South Carolina. Their targeted segments include automotive, distribution and logistics, plastics, life sciences, and advanced materials.

should not be interpreted as suggesting that entrepreneurs considering a high technology venture *move* to regions prone to entrepreneurial activity in the same sector. Instead, the results simply imply that entrepreneurs factor into their decision to start a venture the human capital needs of the business relative to what the local labor market can provide.

First, if a college-educated workforce is required for the venture's success, the entrepreneur must think carefully about how to attract and retain such a workforce. Consider the case of Analytical Graphics, founded in 1989 in Malvern, Pennsylvania, to produce and sell commercial off-the-shelf software for spacecraft and national security applications. To attract and retain a workforce of aerospace, electrical, and software engineers—a comparatively limited workforce pool in the suburbs of Philadelphia—the company offers unusual benefits. Among these is a professional kitchen serving breakfast, lunch, and dinner on a daily basis; a fitness room and laundry room; and arrangement for mundane services like dry cleaning, flower delivery, shoeshines, and oil changes. In return, the company reports that its employee turnover is 3 percent, compared with the industry average of over 20 percent (Von Bergen, 2004).

Second, entrepreneurs looking to launch new ventures in sectors other than business services should weigh carefully the level of self-employment in the county. Per the results in Table 6, the rate of new venture creation in the manufacturing, retail trade, and distributive sectors is lower when the level of self-employment goes up. While this may be the result of would-be entrepreneurs opting for a sole proprietorship or partnership over an incorporated firm with employees, it may also suggest that where self-employment is higher, the pool of available workers to staff new ventures is lower—perhaps too low for the start-up to proceed. This premise is further supported by the generally positive relationship between firm birth rates and the unemployment rate, as well as the negative—albeit negligible—correlation between the share of proprietors and the unemployment rate shown in Table 5. In sum, as is often taught in college entrepreneurship courses, the results imply that entrepreneurs must ensure that the resources needed for the new venture are locally available.

Insights for Research

The insights offered for policy and practice hinge crucially on the validity of the spatial analysis and econometric results. As with most—if not all—empirical studies, there is reason to find fault with the present study. Indeed, despite the care to correctly specify and estimate the empirical model given in Equation 3 by accounting for the spatial and serial correlation and heteroskedasticity of the residuals, there is room for concern and caution. As a case in point, consider the evidence in support of Hypothesis 8 that higher unemployment should lead to higher firm birth rates in the county. The exception in the unemployment relationship is the business services sector. Here, as unemployment goes up, the number of start-ups in the sector goes down. This makes sense in that business services firms are exploiting opportunities to provide *other businesses* with accounting, legal, consulting, and other services. Indeed, if higher unemployment is an indicator of the distress of local businesses, then it follows that any opportunities in the business services sector are fewer as a result.

From a theoretical standpoint, however, this interpretation may indicate that the variables in Equation 3 poorly capture the elements of the knowledge spillover model, such as the source of opportunities, the constraints on these opportunities, the ability and willingness to engage in entrepreneurship, and the quality of local wage and employment conditions. In addition, other important determinants of entrepreneurial activity may be missing entirely from the estimated models, or the method of calculating and transforming the variables may be problematic. In short, as with the analysis by Armington and Acs (2002), the results here should be viewed with caution and interpreted judiciously. In addition, although within-county fixed effects estimates are reported, the relationships between the dependent and independent variables are not necessarily causal.[6] As an example, while spikes in a county's patenting activity are likely to be associated with higher high technology firm birth rates, a host of intervening conditions may prevent this result. In sum, there is ample room for further analysis.

Conclusion

This study set out to explore the extent to which regions within the United States specialize in entrepreneurial activity in particular sectors and the determinants of such specialization. The spatial analysis indicates several pockets of significant start-up activity, including manufacturing in the Pacific-Northwest; retail trade and local market industries in the Rocky Mountain States; high technology industries in California, Massachusetts, and North Carolina; extractive industries in Texas, Oklahoma, and Wyoming; business services in New York, Washington, DC, and Florida; and distributive industries in the plains states. The fascination of scholars and policymakers with high technology start-up activity is justified in that the pattern and determinants of such activity stand apart from the patterns in other sectors. Finally, the implications of the findings for policy, practice, and future research were discussed.

Of course, further analysis using more homogenous industry definitions is possible and warranted. As in the case of South Carolina's Upstate Alliance, efforts to spur start-up activity in fields as different as life sciences and advanced materials may depend on factors unique to each industry. Likewise, further analysis of the spatial outliers—the "oases" of entrepreneurial activity shown in pink on all the LISA cluster maps—is required. One immediately wonders what these counties do or possess in the way of resources that sets them apart from their neighbors. It may be that these oases of entrepreneurial activity hold the key to a complete understanding of where and why enterprises start up in America.

[6] A fixed effects model represents the observed quantities in explanatory variables that are all treated as if those quantities were nonrandom. In contrast, in random effects and mixed models, all or some of the explanatory variables are treated as if they arise from random causes.

Cited Works

Acs, Z. J. & Armington, C. 2004a. The Impact of Geographic Differences in Human Capital on Service Firm Formation Rates. Journal of Urban Economics, 56(2): 244-277.

Acs, Z. J. & Armington, C. 2004b. Employment Growth and Entrepreneurial Activity in Cities. Regional Studies, 38(8): 911-927.

Acs, Z. J., Audretsch, D. B., Braunerhjelm, P., & Carlsson, B. 2005. The Knowledge Spillover Theory of Entrepreneurship, Max Planck Institute. Jena, Germany: Max Planck Institute of Economics.

Ahuja, G. & Katila, R. 2004. Where Do Resources Come From? The Role of Idiosyncratic Situations. Strategic Management Journal, 25(8/9): 887-107.

Almeida, P. 1996. Knowledge Sourcing by Foreign Multinationals: Patent Citation Analysis in the U.S. Semiconductor Industry. Strategic Management Journal, 17(Special Issue): 155-165.

Almeida, P. & Kogut, B. 1999. Localization of Knowledge and the Mobility of Engineers in Regional Networks. Management Science, 45(7): 905-917.

Almeida, P. & Phene, A. 2004. Subsidiaries and Knowledge Creation: The Influence of the MNC and Host Country on Innovation. Strategic Management Journal, 25(8/9): 847-864.

Anselin, L. 1995. Local Indicators of Spatial Association - LISA. Geographical Analysis, 27(2): 93-115.

Anselin, L. & Bera, A. K. 1998. Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics. In A. Ullah & D. Giles (Eds.), Handbook of Applied Economic Statistics: 237-246. New York: Marcel Dekker.

Anselin, L., Varga, A., & Acs, Z. J. 2000. Geographical Spillovers and University Research: A Spatial Econometric Perspective. Growth & Change, 31(4): 501-515.

Anselin, L. 2001. Spatial Econometrics. In B. Baltagi (Ed.), A Companion to Theoretical Econometrics: 310-330. Oxford: Basil Blackwell.

Anselin, L., Syabri, I., & Smirnov, O. 2002. Visualizing Multivariate Spatial Correlation with Dynamically Linked Windows, Spatial Analysis Laboratory, University of Illinois - Urbana/Champaign. Urbana, Il.

Anselin, L., Syabri, I., & Kho, Y. 2006. Geoda: An Introduction to Spatial Data Analysis. Geographical Analysis, 38(1): 5-22.

Armington, C. & Acs, Z. J. 2002. The Determinants of Regional Variation in New Firm Formation. Regional Studies, 36(1): 33-45.

Audretsch, D. B. & Fritsch, M. 1994. On the Measurement of Entry Rates. Empirica, 21(1): 105-113.

Audretsch, D. B. 2000. Entrepreneurship in Germany. In D. L. Sexton & H. Landstrom (Eds.), Handbook of Entrepreneurship: 107-127. Oxford: Blackwell Publishers.

Audretsch, D. B., Keilbach, M. C., & Lehmann, E. E. 2006. Entrepreneurship and Economic Growth. Oxford: Oxford University Press.

Baum, J. A. C. & Oliver, C. 1996. Toward an Institutional Ecology of Organizational Founding. Academy of Management Journal, 39(5): 1378-1427.

Casson, M. C. 2003. Entrepreneurship, Business Culture and the Theory of the Firm. In Z. J. Acs & D. B. Audretsch (Eds.), Handbook of Entrepreneurship Research: 223-246. Boston: Kluwer.

Chang, S.-J. & Park, S. 2005. Types of Firms Generating Network Externalities in MNC's Co-Location Decisions. Strategic Management Journal, 26(7): 595-615.

Chung, W. & Alcácer, J. 2002. Knowledge Seeking and Location Choice of Foreign Direct Investment in the United States. Management Science, 48(12): 1534-1554.

Cooper, A. C. & Folta, T. B. 2000. Entrepreneurship in High-Technology Clusters. In D. L. Sexton & H. Landstrom (Eds.), Handbook of Entrepreneurship: 348-367. Malden, MA: Blackwell.

DeCarolis, D. M. & Deeds, D. L. 1999. The Impact of Stocks and Flows of Organizational Knowledge on Firm Performance: An Empirical Investigation of the Biotechnology Industry. Strategic Management Journal, 20(10): 953-968.

Doh, J. P. & Hahn, E. D. 2008. Using Spatial Methods in Strategy Research. Organizational Research Methods, 11(4): 659-681.

Driscoll, J. C. & Kraay, A. C. 1998. Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data. Review of Economics and Statistics, 80(4): 549-560.

Dumais, G., Ellison, G., & Glaeser, E. L. 2002. Geographic Concentration as a Dynamic Process. Review of Economics and Statistics, 84(2): 193-204.

Gibbons, D. E. 2004. Network Structure and Innovation Ambiguity Effects on Diffusion in Dynamic Organizational Fields. Academy of Management Journal, 47(6): 938-951.

Henderson, J. V. 2003. Marshall's Scale Economies. Journal of Urban Economics, 53(1): 1-28.

Hoechle, D. 2007. Robust Standard Errors for Panel Regressions with Cross-Sectional Dependence. Stata Journal, 7(3): 281-312.

Lomi, A. 1995. The Population Ecology of Organizational Founding: Location Dependence and Unobserved Heterogeneity. Administrative Science Quarterly, 40(1): 111-144.

Marchington, M., Carroll, M., & Boxall, P. 2003. Labour Scarcity and the Survival of Small Firms: A Resource-Based View of the Road Haulage Industry. Human Resource Management Journal, 13(4): 5-22.

McCann, B. T. & Folta, T. B. 2008. Location Matters: Where We Have Been and Where We Might Go in Agglomeration Research. Journal of Management, 34(3): 532-565.

Mugler, J. 2000. The Climate for Entrepreneurship in European Countries in Transition. In D. L. Sexton & H. Landstrom (Eds.), Handbook of Entrepreneurship: 150-175. Oxford: Blackwell Publishers.

Parker, S. C. 2004. The Economics of Self-Employment and Entrepreneurship. Cambridge: Cambridge University Press.

Pe'er, A. & Vertinsky, I. 2008. Firm Exits as a Determinant of New Entry: Is There Evidence of Local Creative Destruction? Journal of Business Venturing, 23(3): 280-306.

Perry, M. J. & Mackun, P. 2001. Population Change and Distribution, Census 2000 Brief, US Census Bureau. Washington, DC.

Phene, A. & Almeida, P. 2003. How Do Firms Evolve? The Patterns of Technological Evolution of Semiconductor Subsidiaries. International Business Review, 12(3): 349-367.

Plummer, L. A. & Headd, B. 2007. Rural and Urban Establishment Births and Deaths Using the Us Census Bureau's Business Information Tracking Series, Small Business Administration, Office of Advocacy. Washington, DC.

Plummer, L. A. 2010. Spatial Dependence in Entrepreneurship Research: Challenges and Methods. Organizational Research Methods, 13(1): 146-175.

Quello, S. & Toft, G. 2006. Economic Gardening: Next Generation Applications for a Balanced Portfolio Approach to Economic Growth, The Small Business Economy: A Report to the President: 157-190. Washington, DC: Small Business Administration, Office of Advocacy.

Romer, P. M. 1986. Increasing Returns and Long Run Growth. Journal of Political Economy, 94(5): 1002-1037.

Romer, P. M. 1987. Growth Based on Increasing Returns Due to Specialization. American Economic Review, 77(2): 56-72.

Romer, P. M. 1990. Endogenous Technological Change. Journal of Political Economy, 98(5): S71-S102.

Rumelt, R. P. 1987. Theory, Strategy, and Entrepreneurship. In D. J. Teece (Ed.), The Competitive Challenge: 137-158. New York: Harper & Row.

Russo, M. V. 2003. The Emergence of Sustainable Industries: Building on Natural Capital. Strategic Management Journal, 24(4): 317-331.

Shane, S. & Venkataraman, S. 2000. The Promise of Entrepreneurship as a Field of Research. Academy of Management Review, 25(1): 217-226.

Song, J., Almeida, P., & Wu, G. 2003. Learning-by-Hiring: When Is Mobility More Likely to Facilitate Interfirm Knowledge Transfer? Management Science, 49(4): 351-365.

Sorenson, O. & Audia, P. G. 2000. The Social Structure of Entrepreneurial Activity: Geographic Concentration of Footwear Production in the United States, 1940-1989. American Journal of Sociology, 106(2): 424-461.

Sorenson, O. & Stuart, T. E. 2001. Syndication Networks and the Spatial Distribution of Venture Capital Investments. American Journal of Sociology, 106(6): 1546-1588.

Sorenson, O. 2003. Social Networks and Industrial Geography. Journal of Evolutionary Economics, 13(5): 513-527.

Storey, D. 2000. Six Steps to Heaven: Evaluating the Impact of Public Policies to Support Small Business in Developed Economies. In D. L. Sexton & H. Landstrom (Eds.), Handbook of Entrepreneurship: 177-193. Oxford: Blackwell Publishers.

Varga, A. 1998. University Research and Regional Innovation: A Spatial Econometric Analysis of Academic Technology Transfer. Boston: Kluwer.

Varga, A. 2000. Local Academic Knowledge Transfers and the Concentration of Economic Activity. Journal of Regional Science, 40: 289.

Venkataraman, S. 1997. The Distinctive Domain of Entrepreneurship Research. In J. A. Katz (Ed.), Advances in Entrepreneurship, Firm Emergence and Growth, Vol. Volume 3: 119-138. Greenwich, CT: JAI Press.

Venkataraman, S. 2004. Regional Transformation through Technological Entrepreneurship. Journal of Business Venturing, 19(1): 153-167.

Von Bergen, J. M. 2004. Happiness Equals Productivity, Philadelphia Inquirer: D1. Philadelphia.

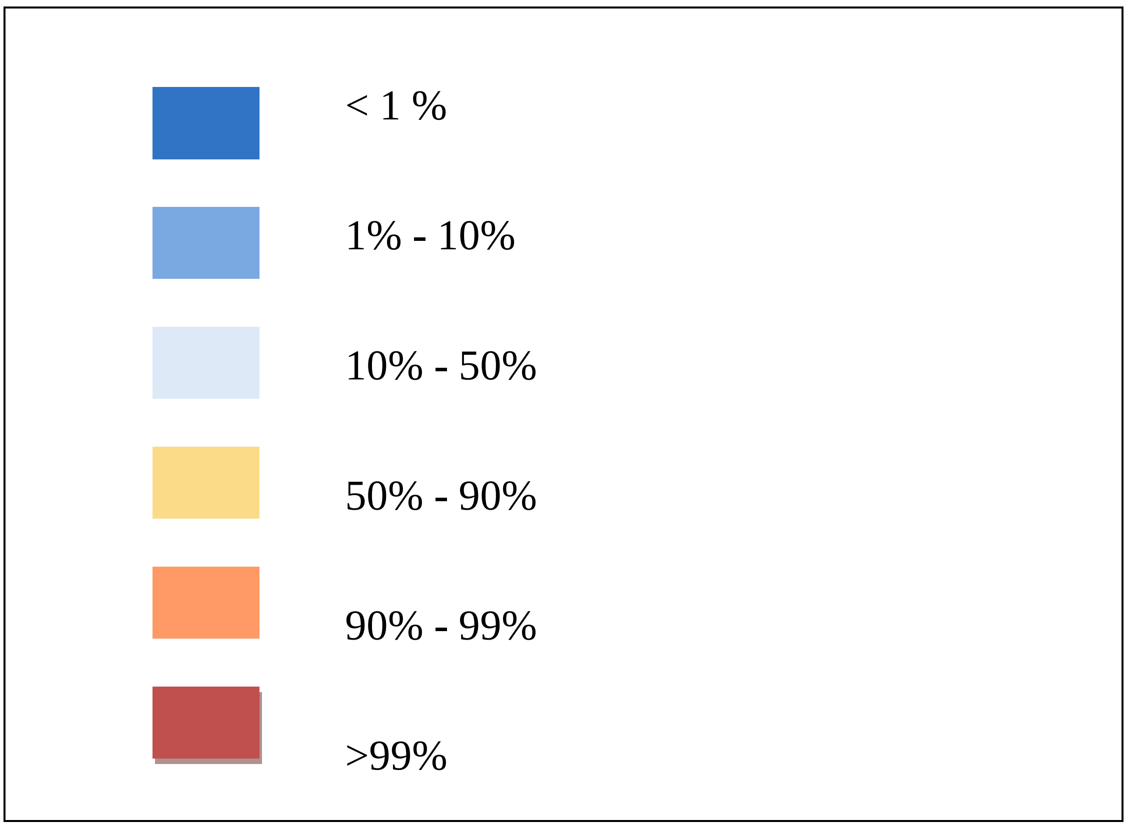
Zucker, L. G., Darby, M. R., & Armstrong, J. S. 2002. Commercializing Knowledge: University Science, Knowledge Capture, and Firm Performance in Biotechnology. Management Science, 48(1): 138-153.

Figures

(All figures are color images.)

Percentile Maps

Legend 1: Percentile Maps



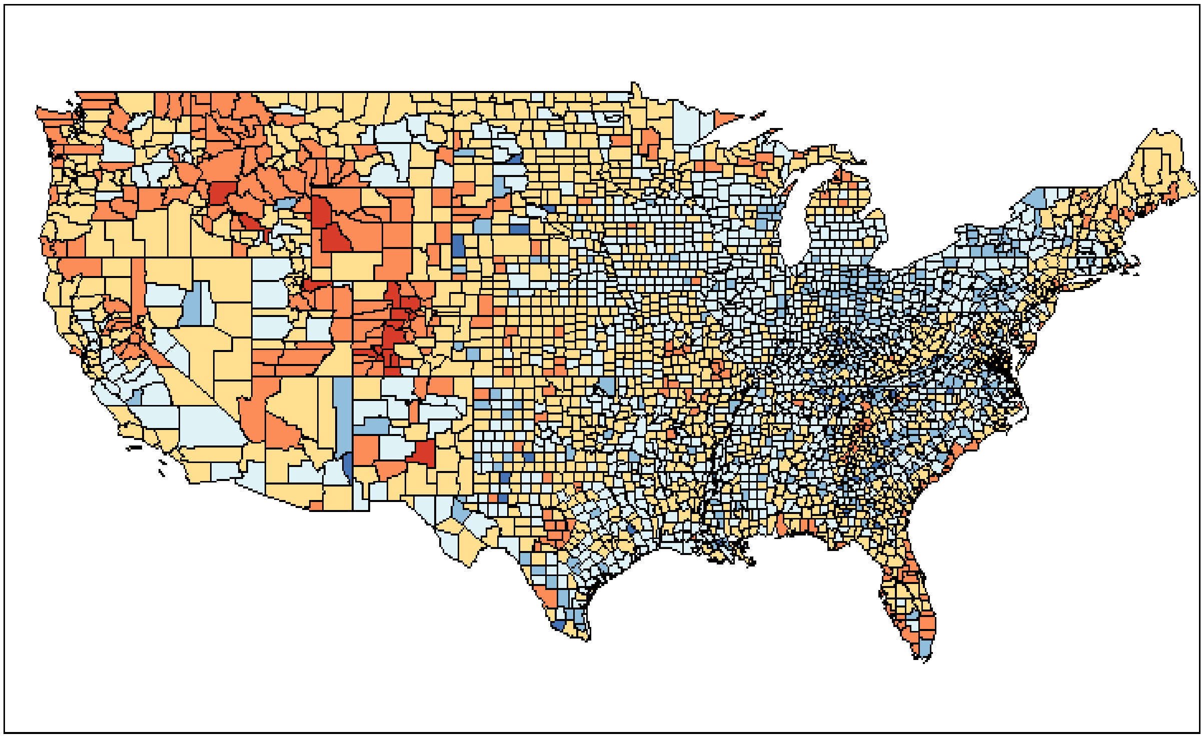


Figure 1: Percentile Map of All Sectors

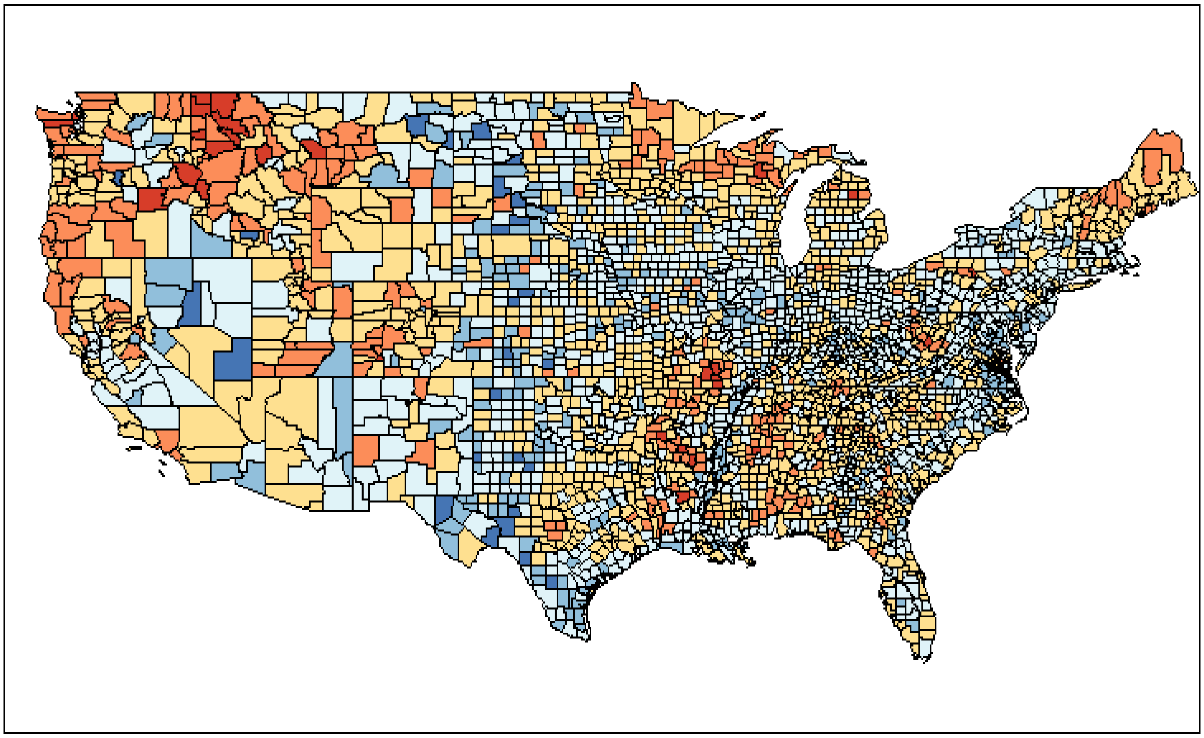


Figure 2: Percentile Map of Manufacturing Industries

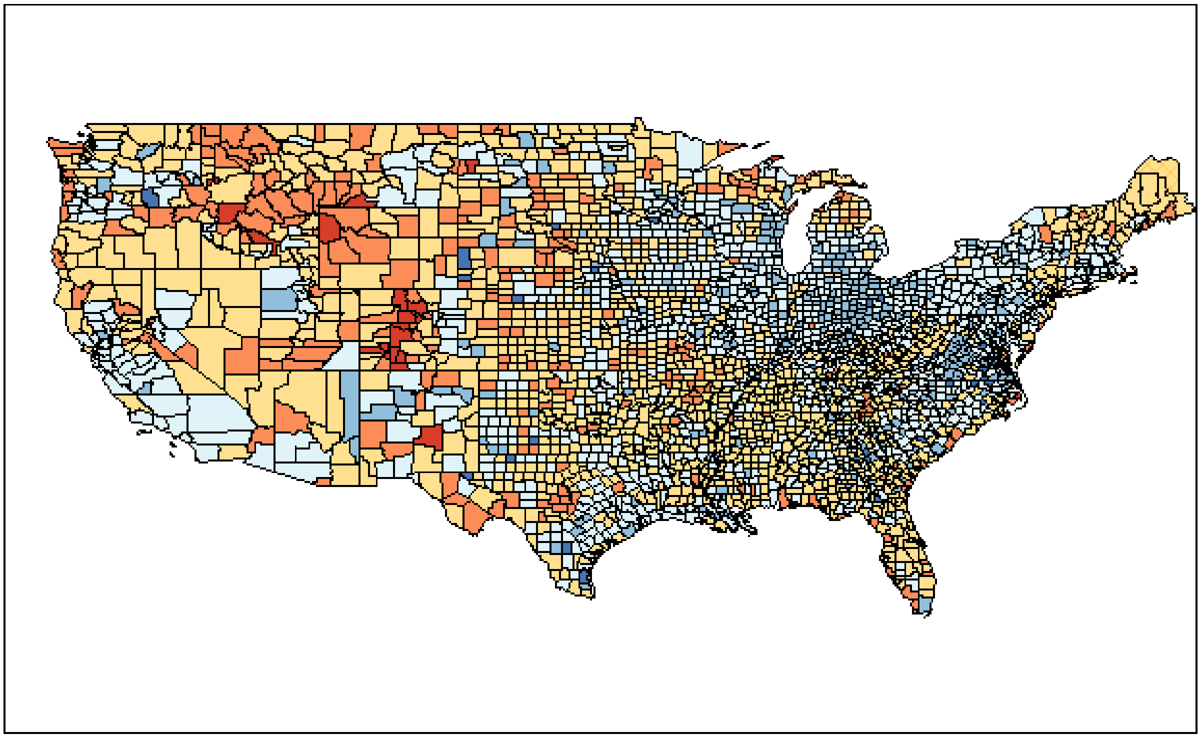


Figure 3: Percentile Map of Retail Trade Industries

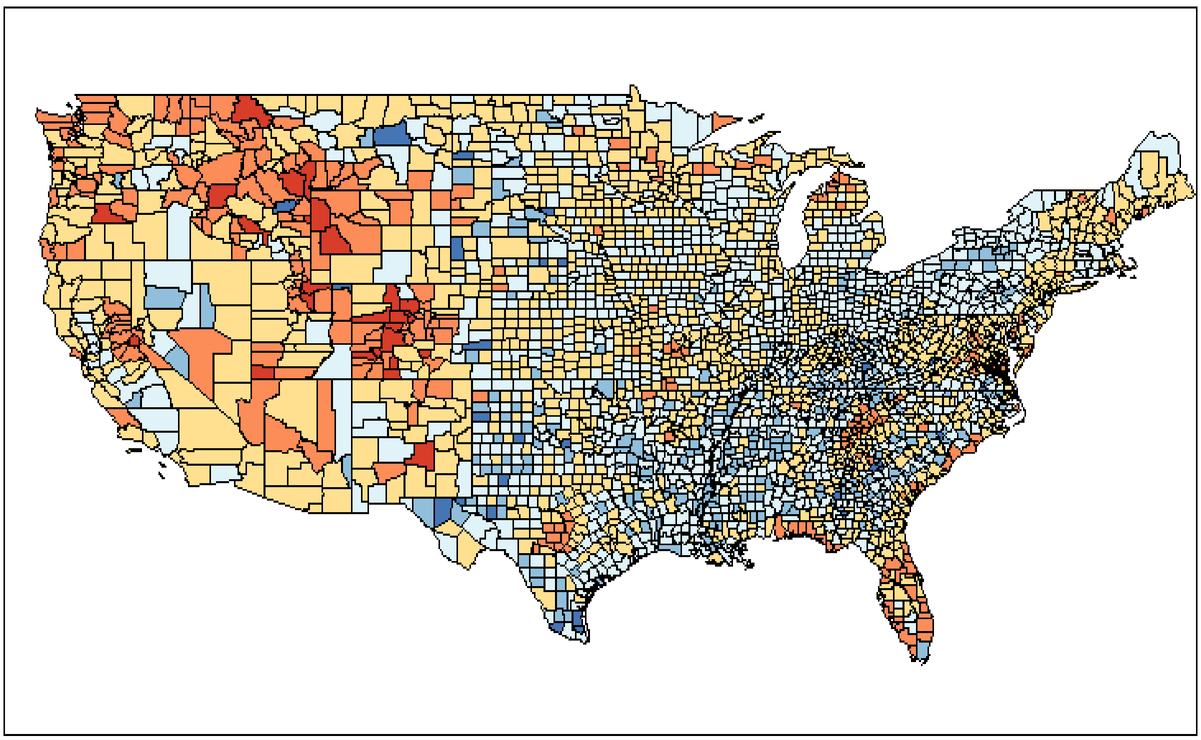


Figure 4: Percentile Map of Local Market Industries

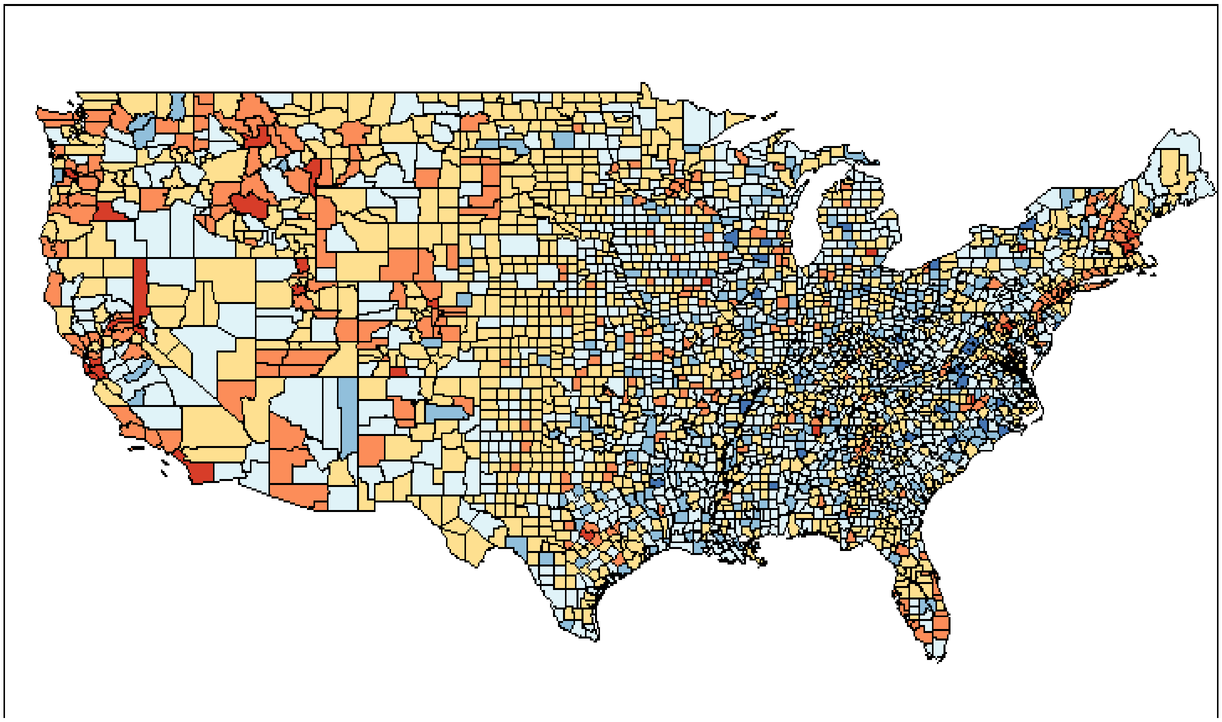


Figure 5: Percentile Map of High Tech Industries

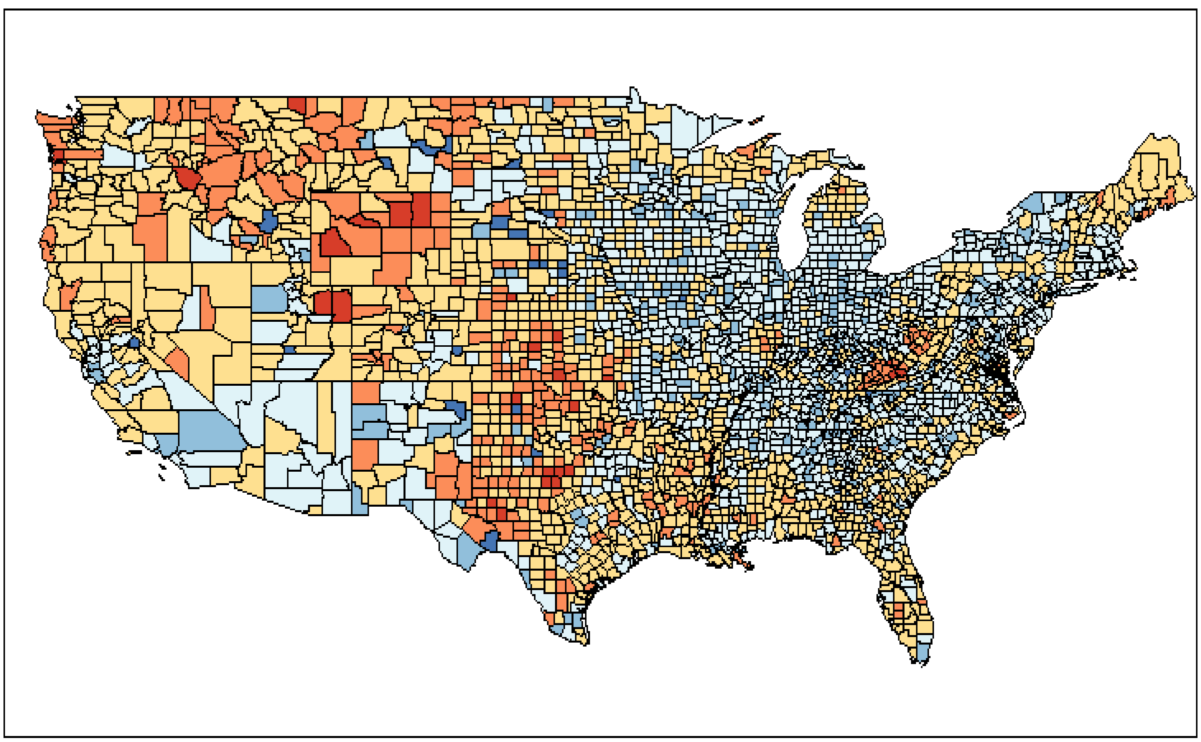


Figure 6: Percentile Map of Extractive Industries

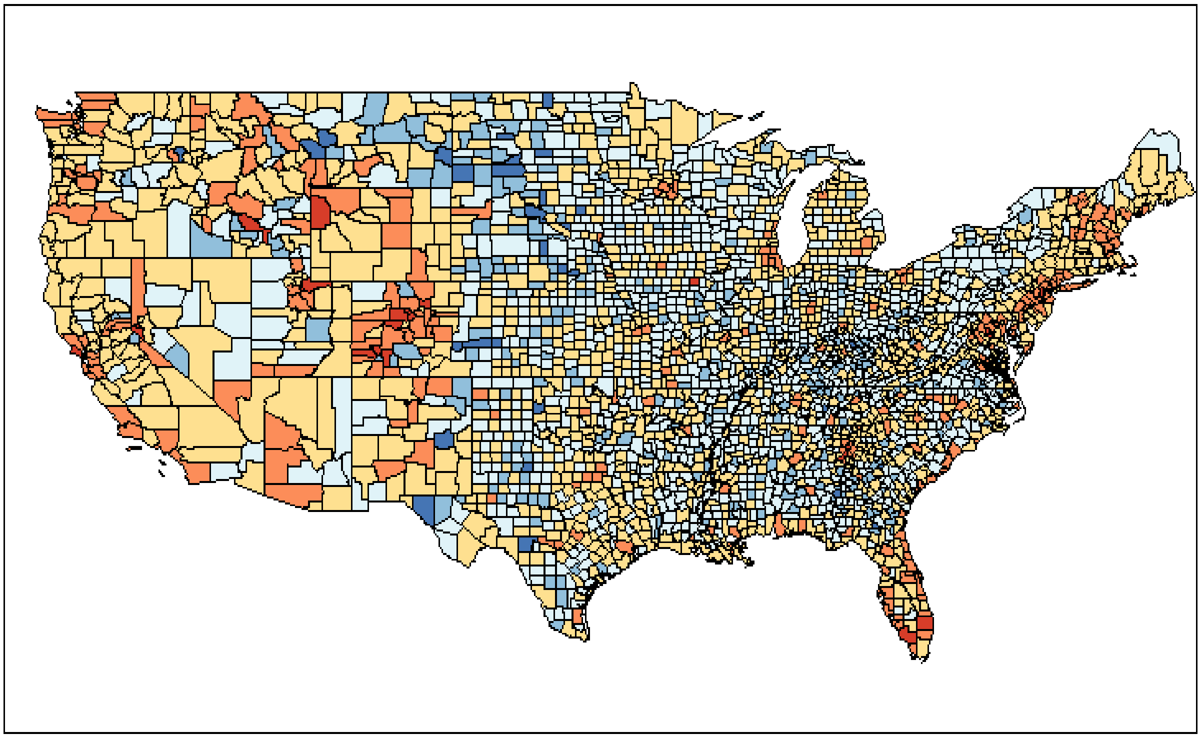


Figure 7: Percentile Map of Business Service Industries (1990-1998)

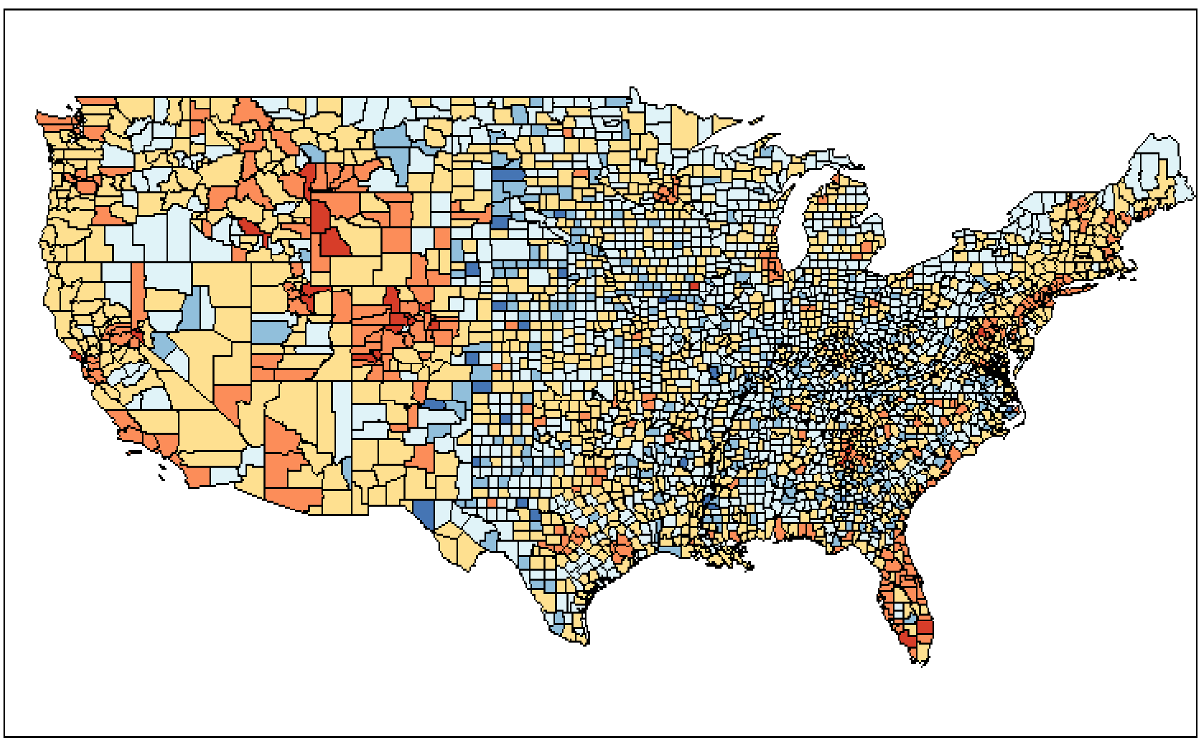


Figure 8: Percentile Map of Business Service Industries (1999-2006)

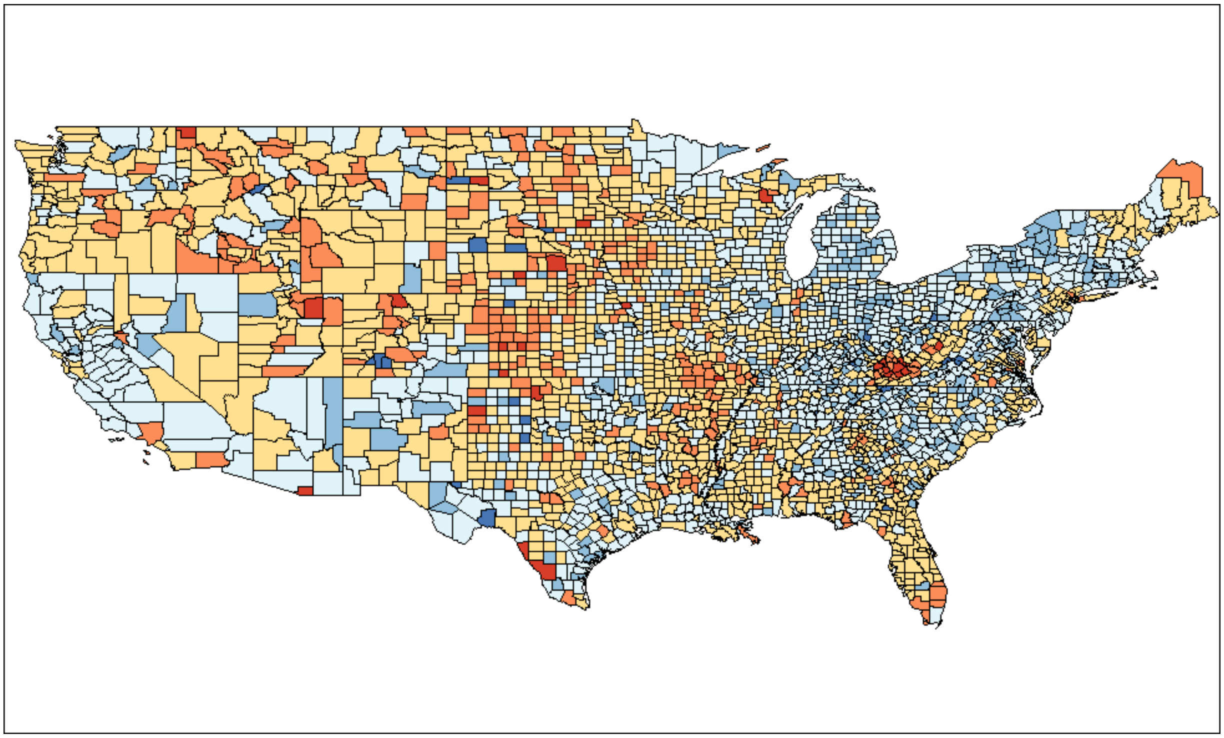
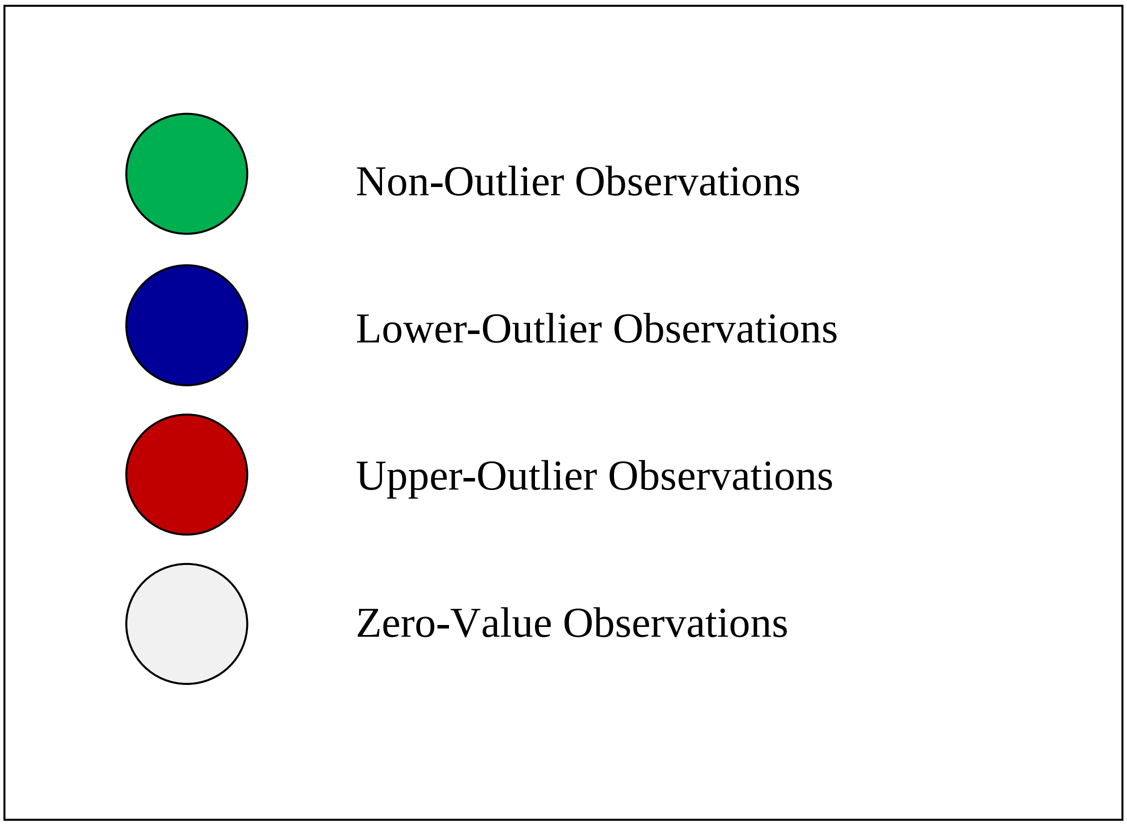


Figure 9: Percentile Map of Distributive Industries

Circular Cartograms

Legend 2: Circular Cartogram Maps



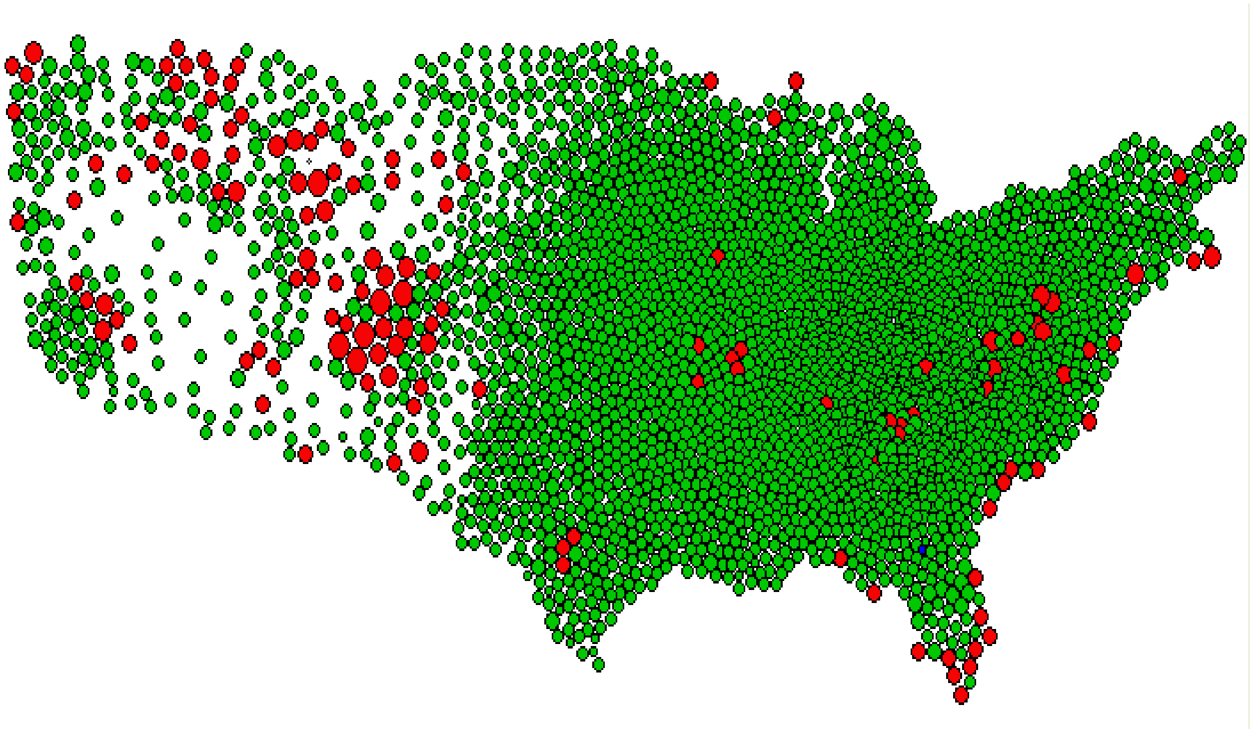


Figure 10: Cartogram of All Sectors

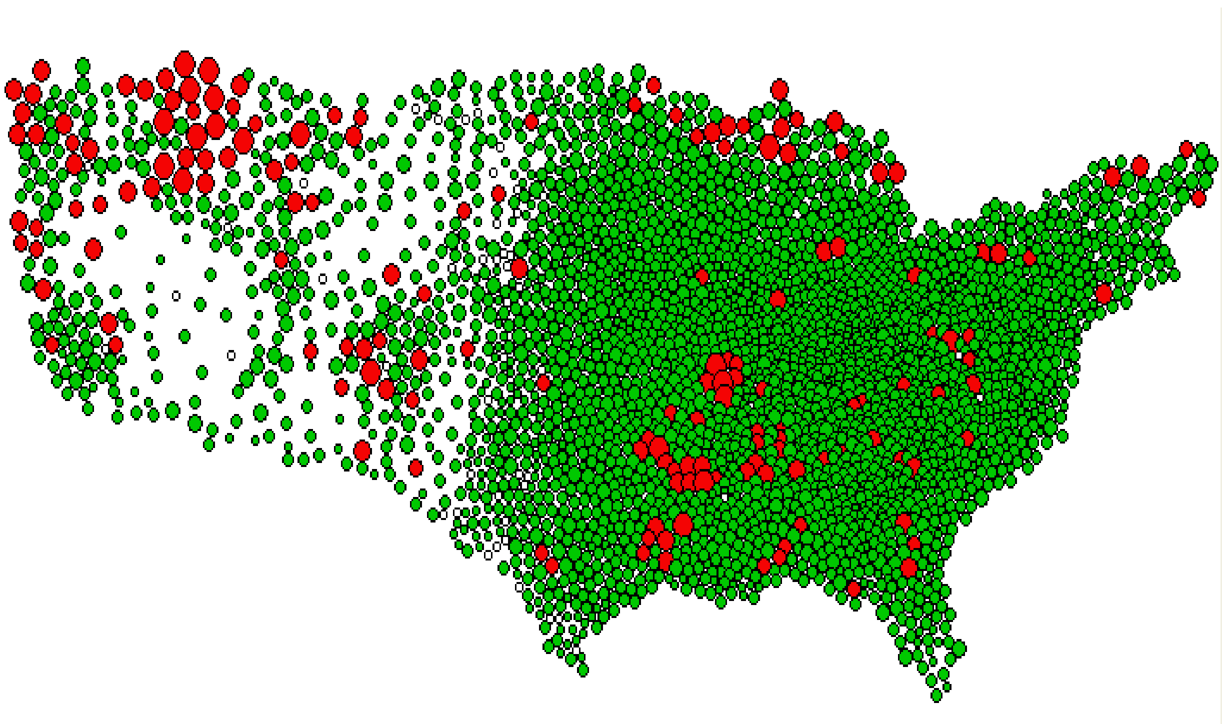


Figure 11: Cartogram of Manufacturing Industries

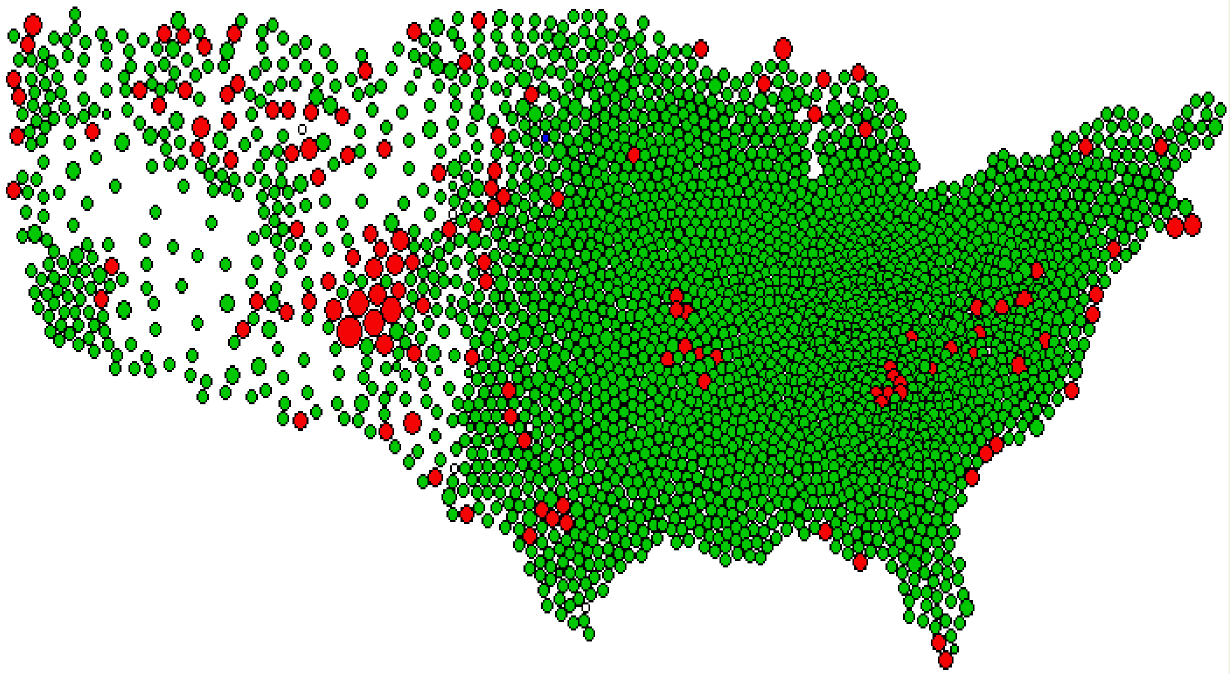


Figure 12: Cartogram of Retail Trade Industries

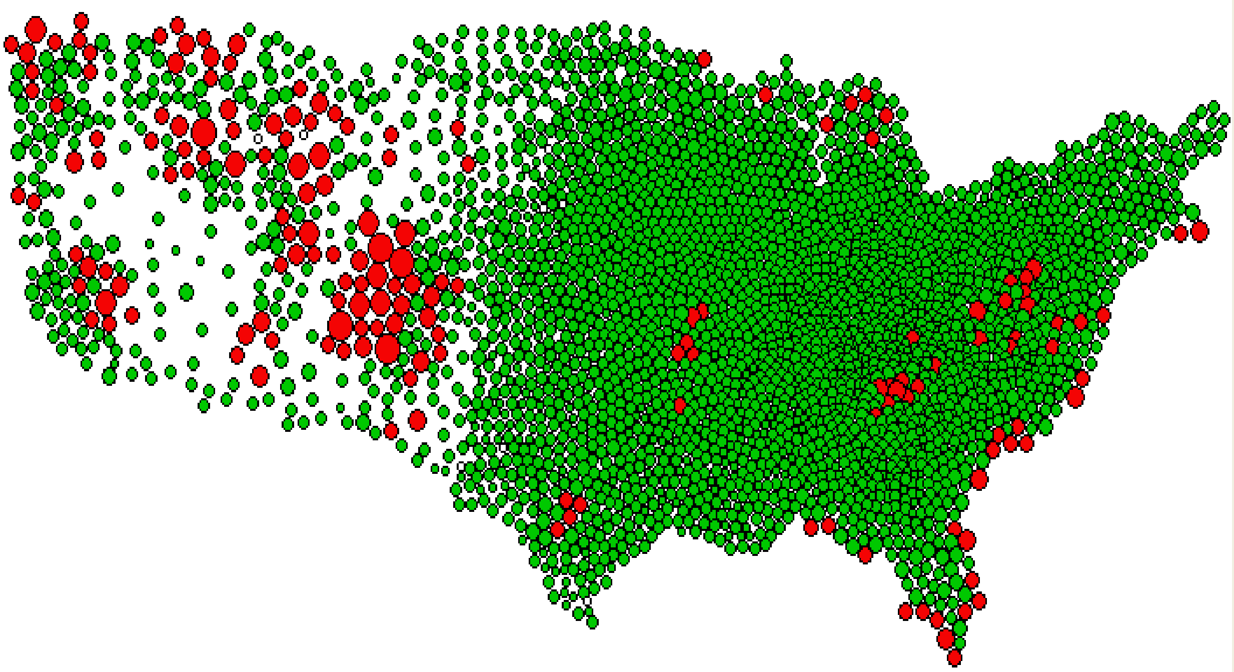


Figure 13: Cartogram of Local Market Industries

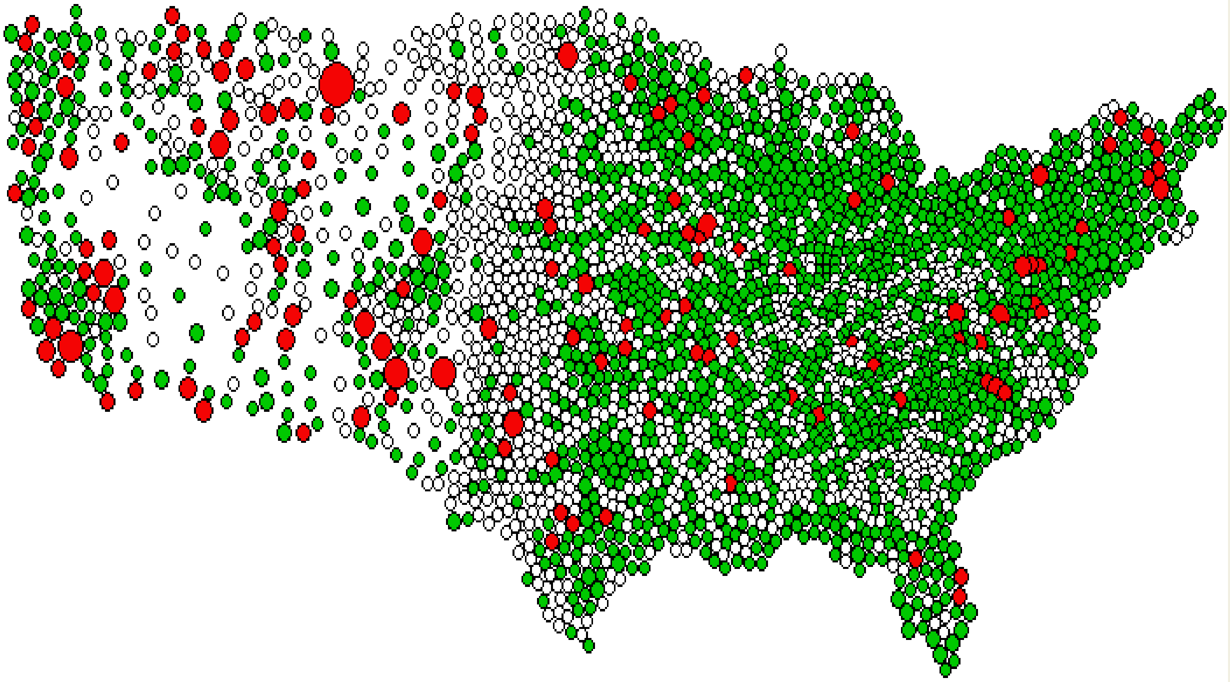


Figure 14: Cartogram of High Tech Industries

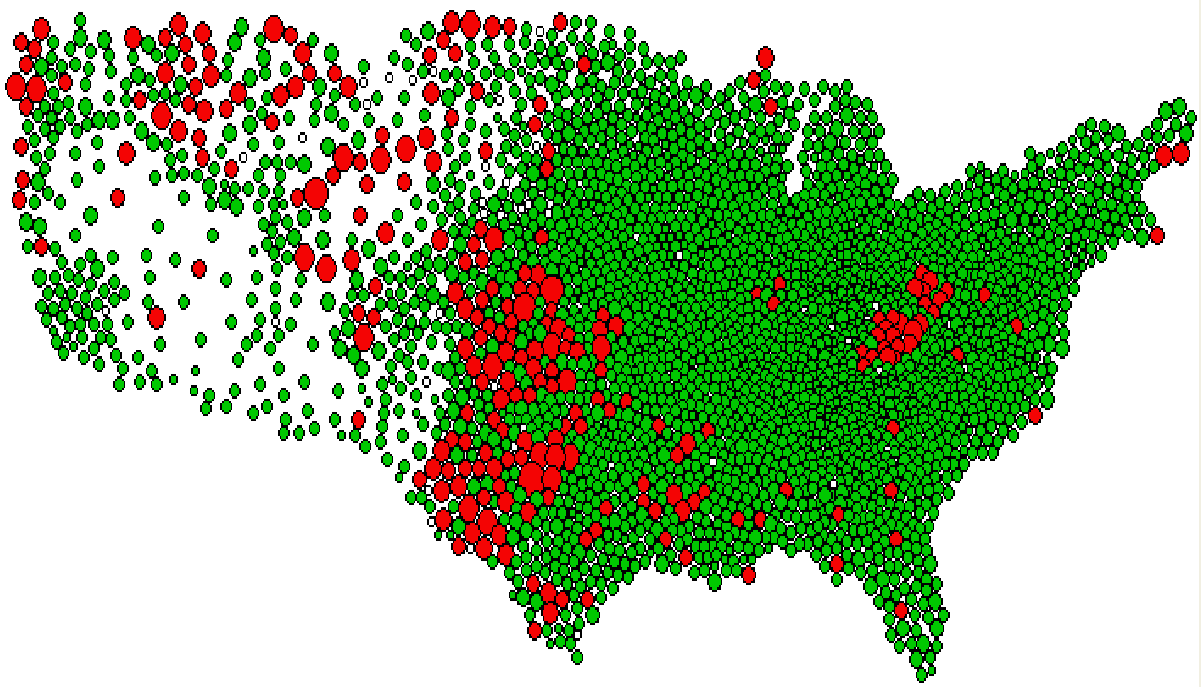


Figure 15: Cartogram of Extractive Industries

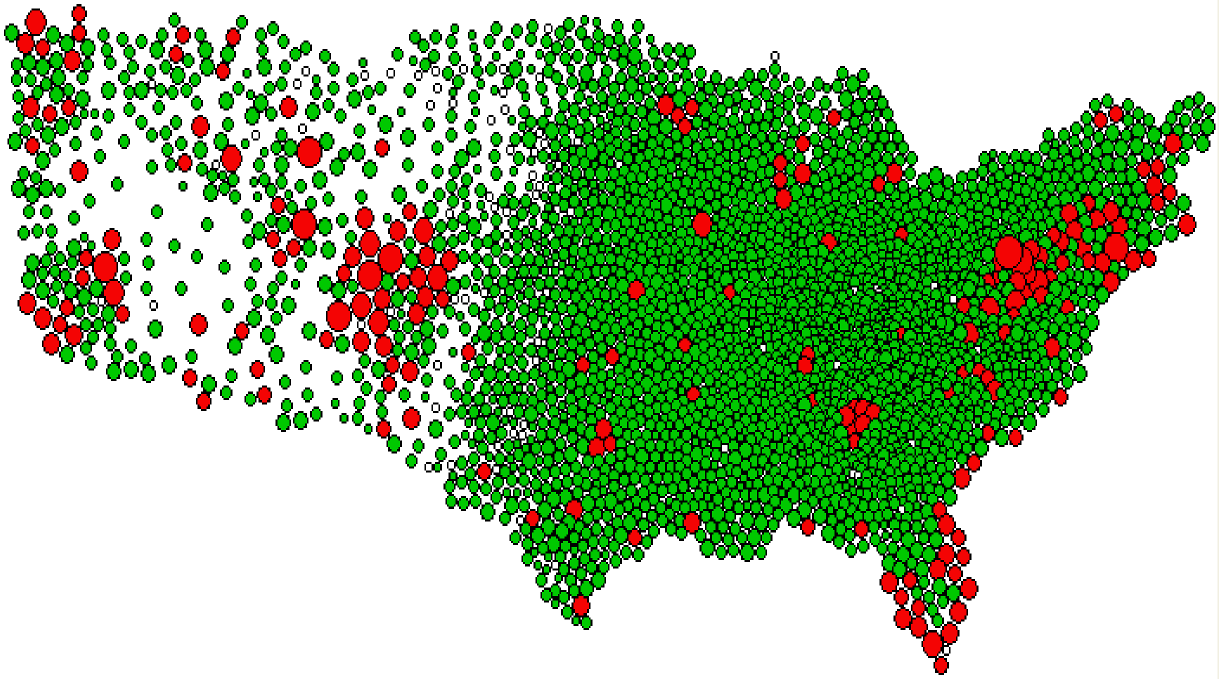


Figure 16: Cartogram of Business Service Industries (1990-1998)

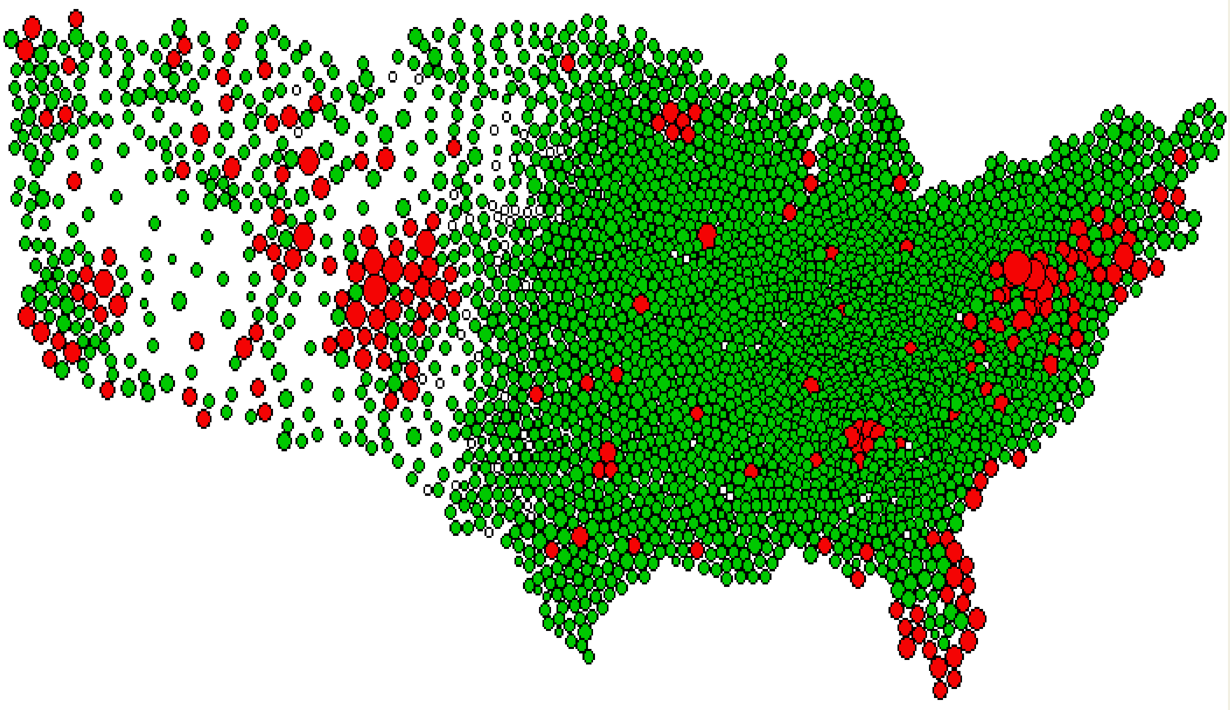


Figure 17: Cartogram of Business Service Industries (1999-2006)

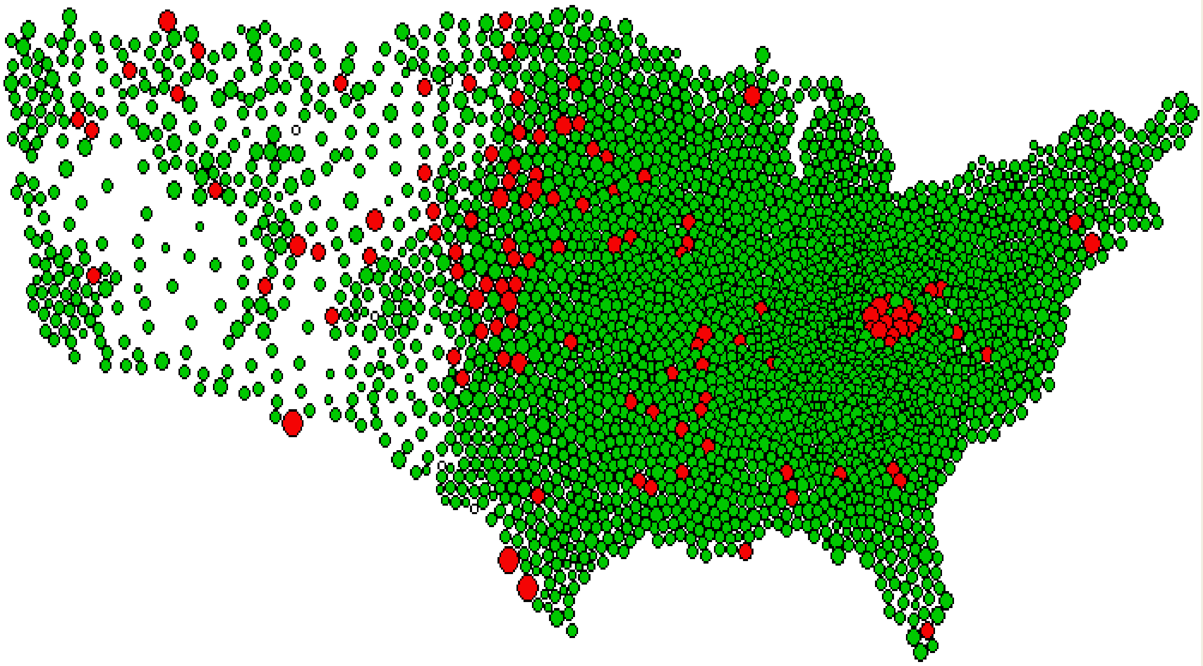
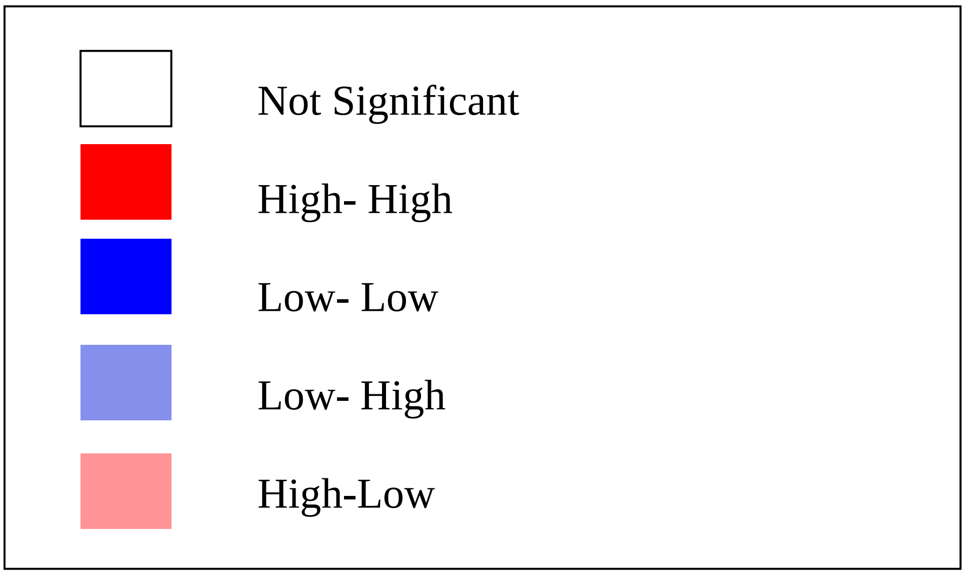


Figure 18: Cartogram of Distributive Industries

LISA Cluster Maps

Legend 3: LISA Cluster Maps



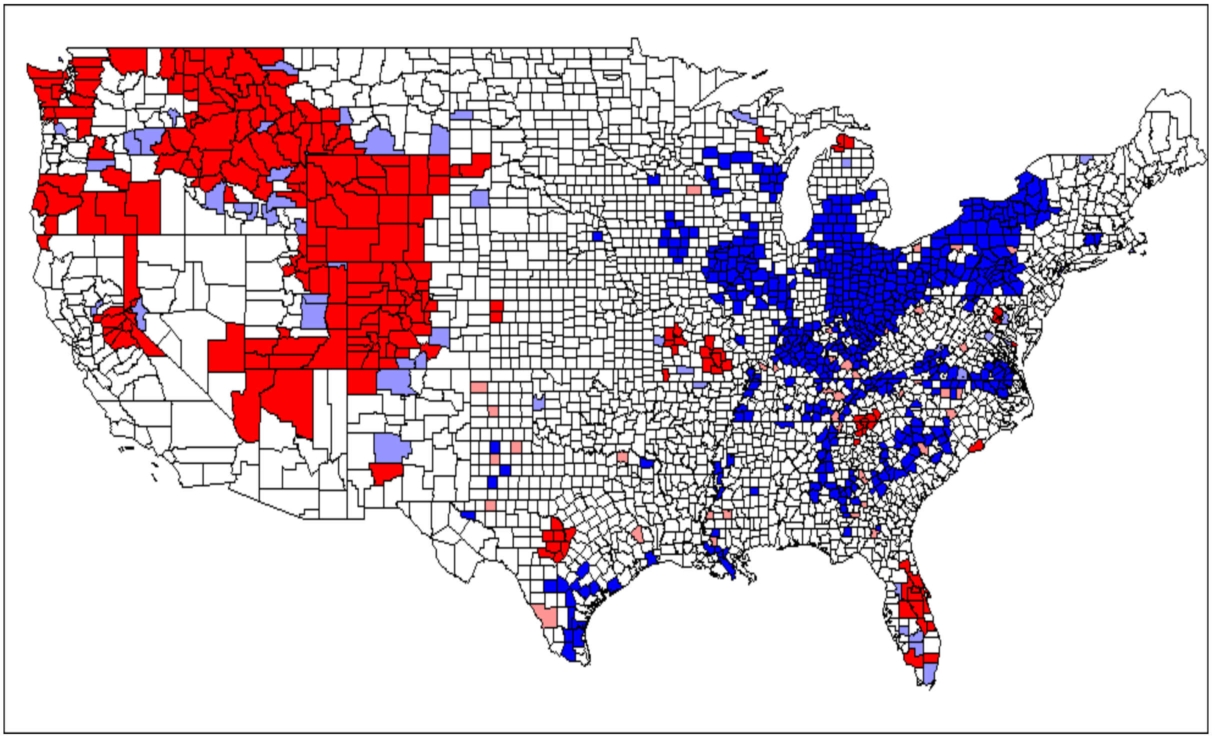


Figure 19: LISA Cluster Map of All Sectors (Moran's I = 0.44, p < 0.01)

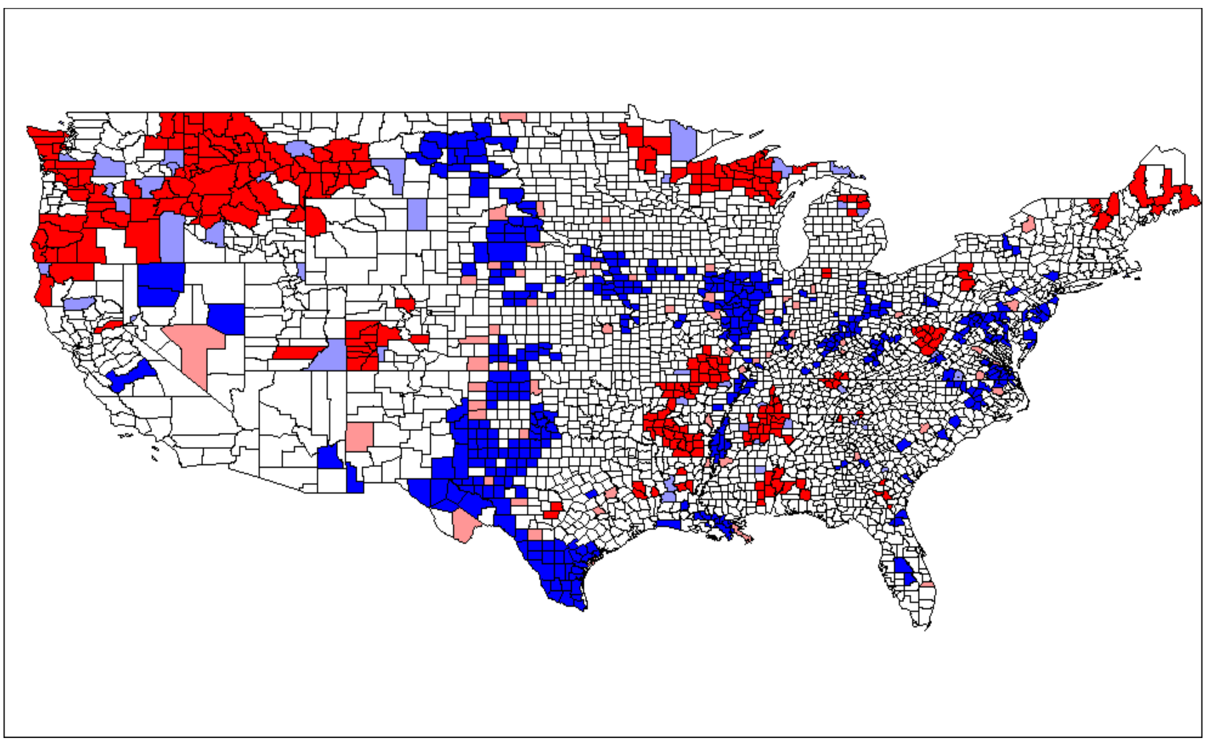


Figure 20: LISA Cluster Map of Manufacturing Industries (Moran's I = 0.40, p < 0.01)

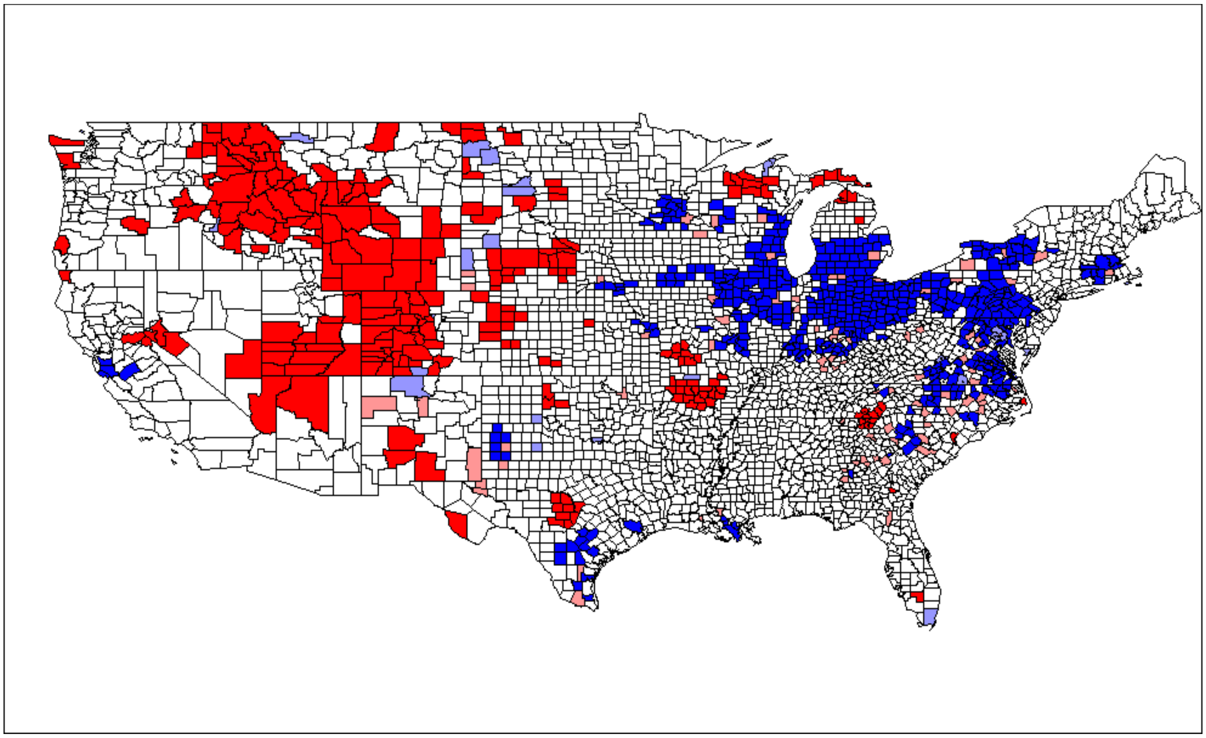


Figure 21: LISA Cluster Map of Retail Trade Industries (Moran's I = 0.36, p < 0.01)

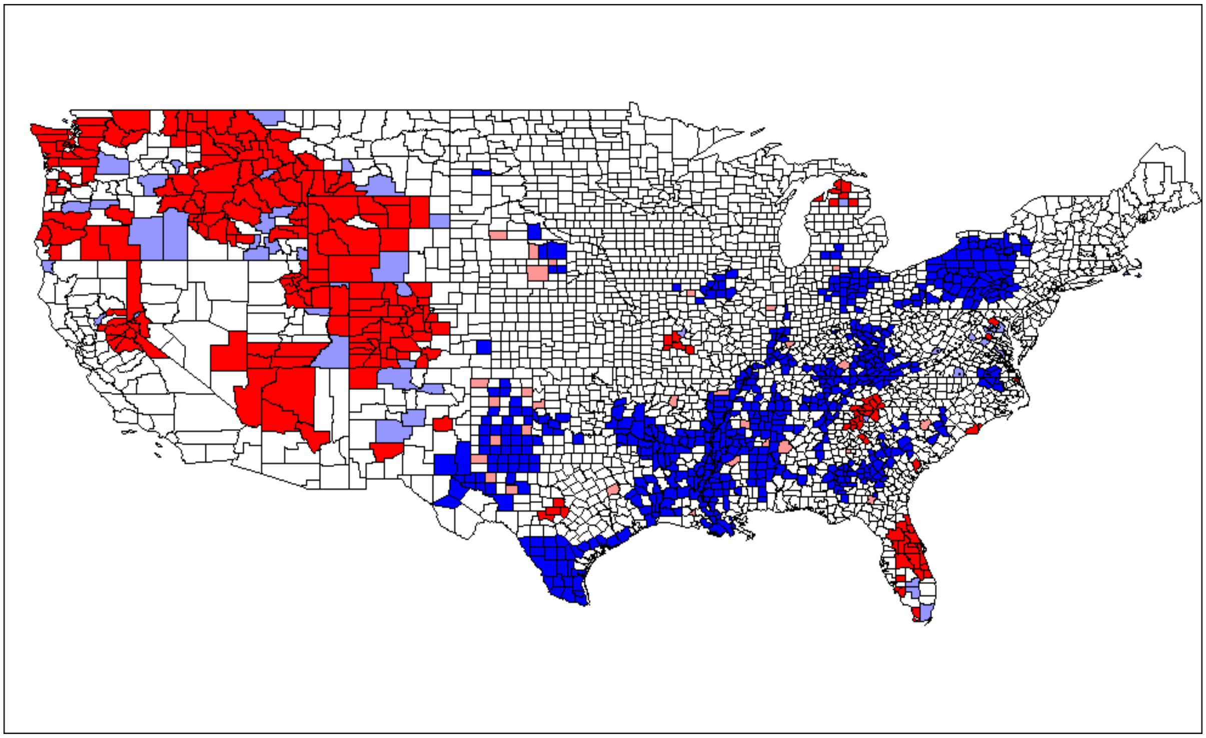


Figure 22: LISA Cluster Map of Local Market Industries (Moran's I = 0.47, p < 0.01)

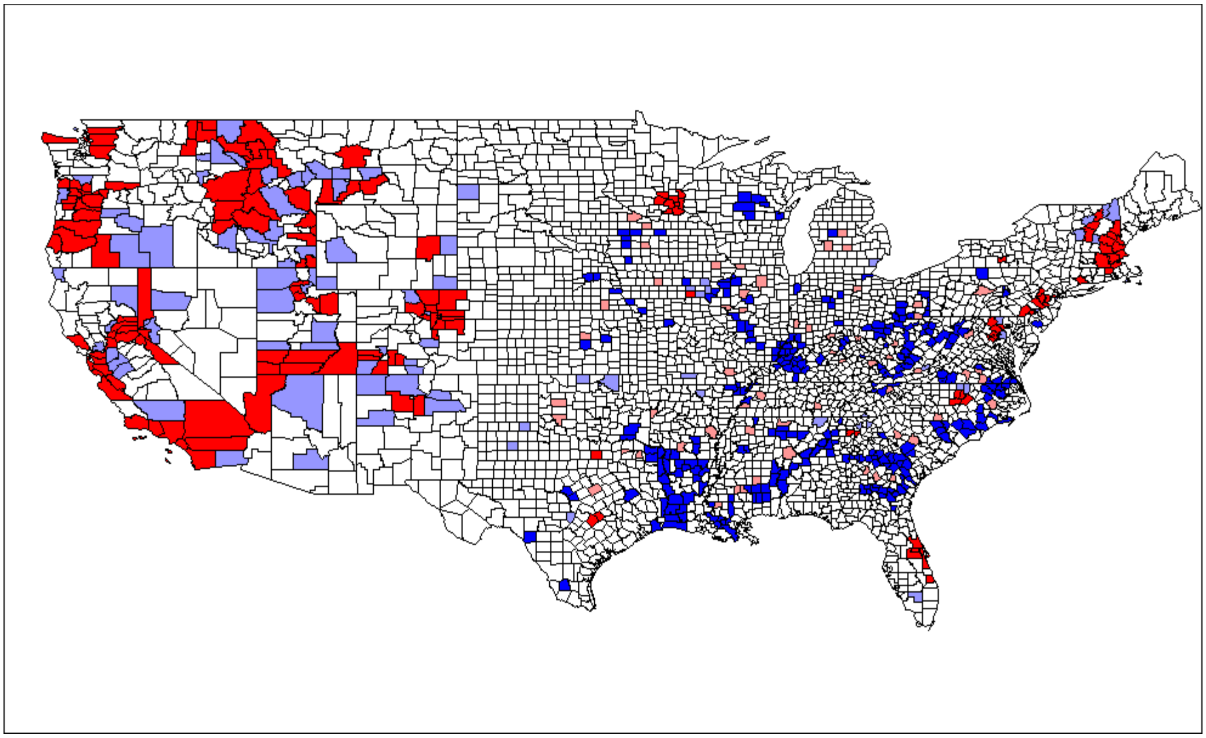


Figure 23: LISA Cluster Map of High Tech Industries (Moran's I = 0.14, p < 0.01)

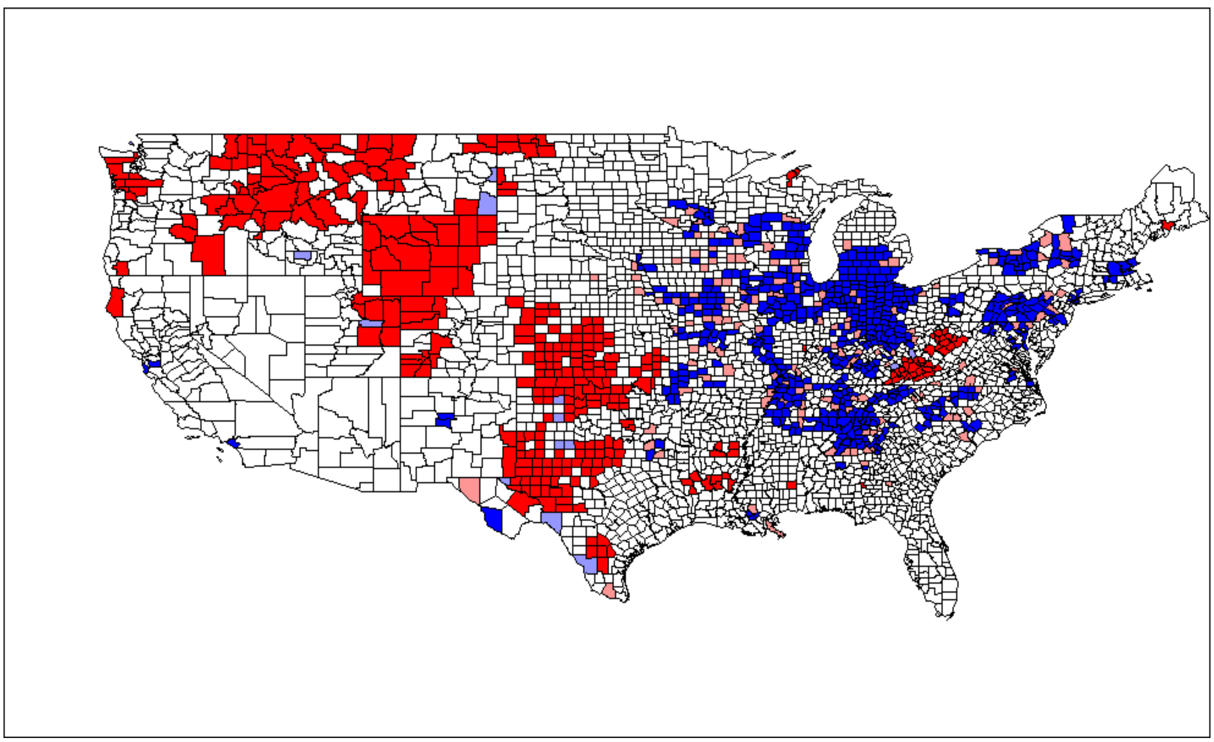


Figure 24: LISA Cluster Map of Extractive Industries (Moran's I = 0.43, p < 0.01)

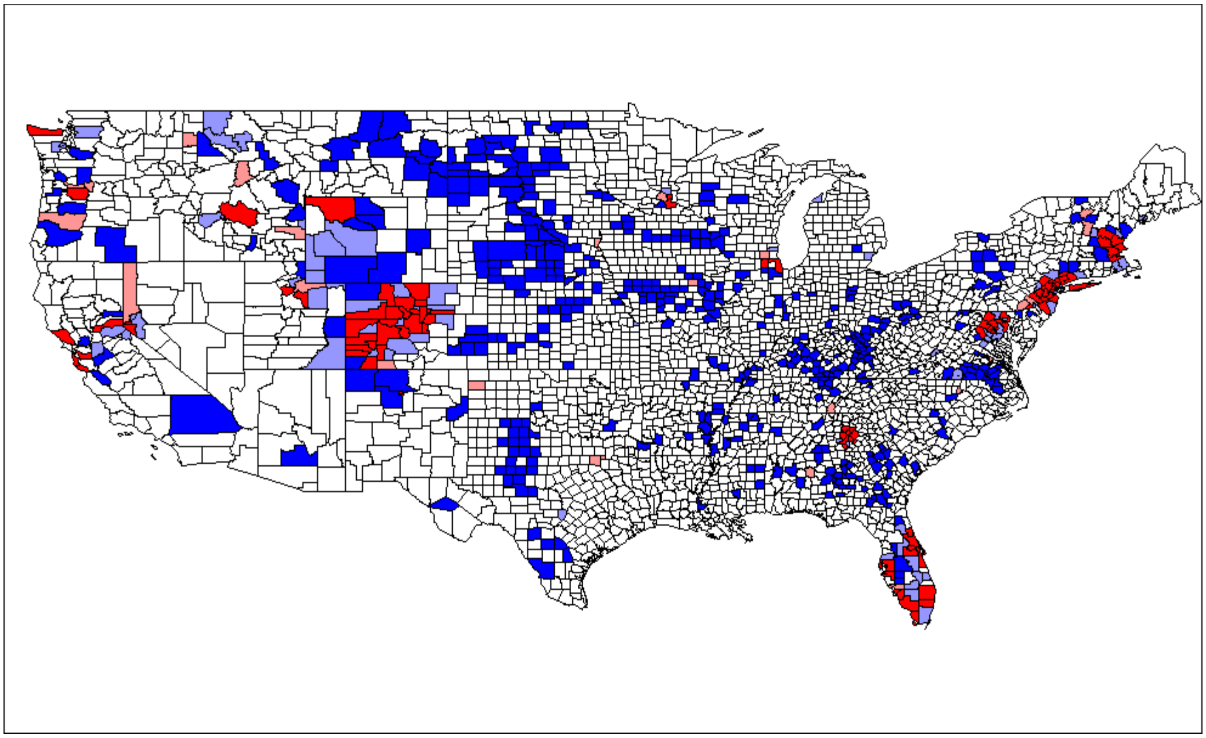


Figure 25: LISA Cluster Map of Business Services (1990-1998) (Moran's I = 0.37, p < 0.01)

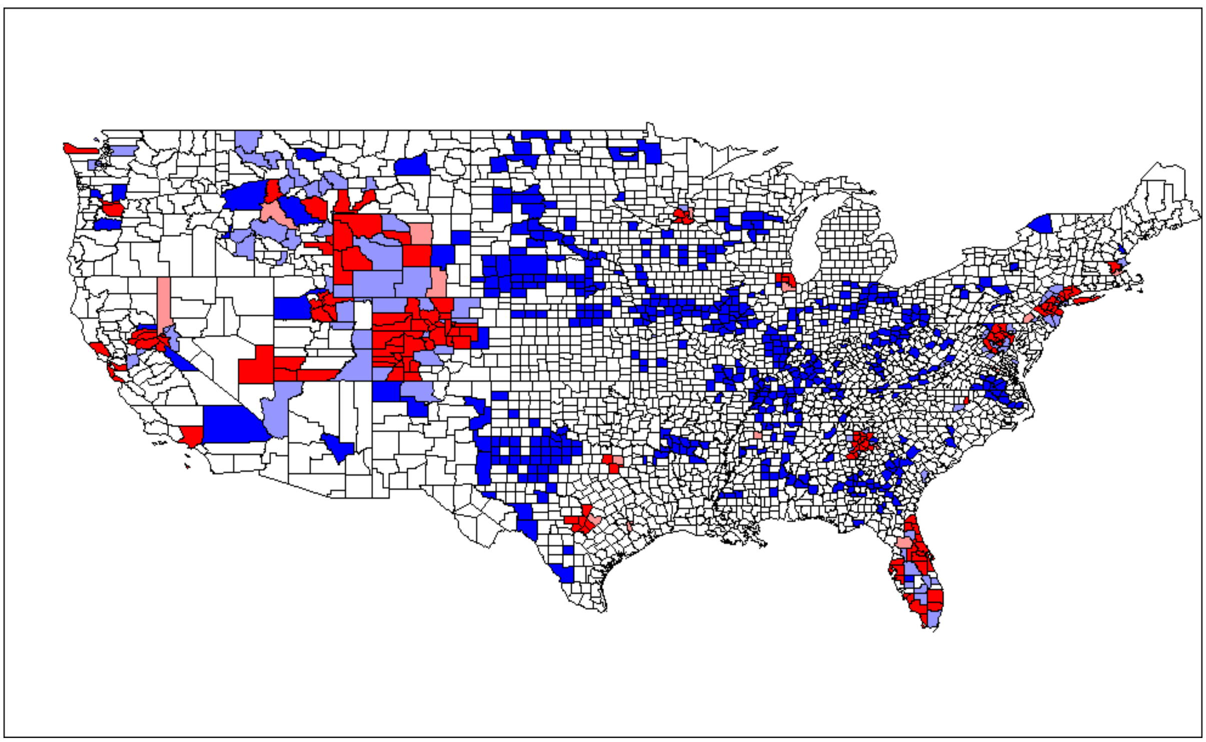


Figure 26: LISA Cluster Map of Business Services (1999-2006) (Moran's I = 0.40, p < 0.01)

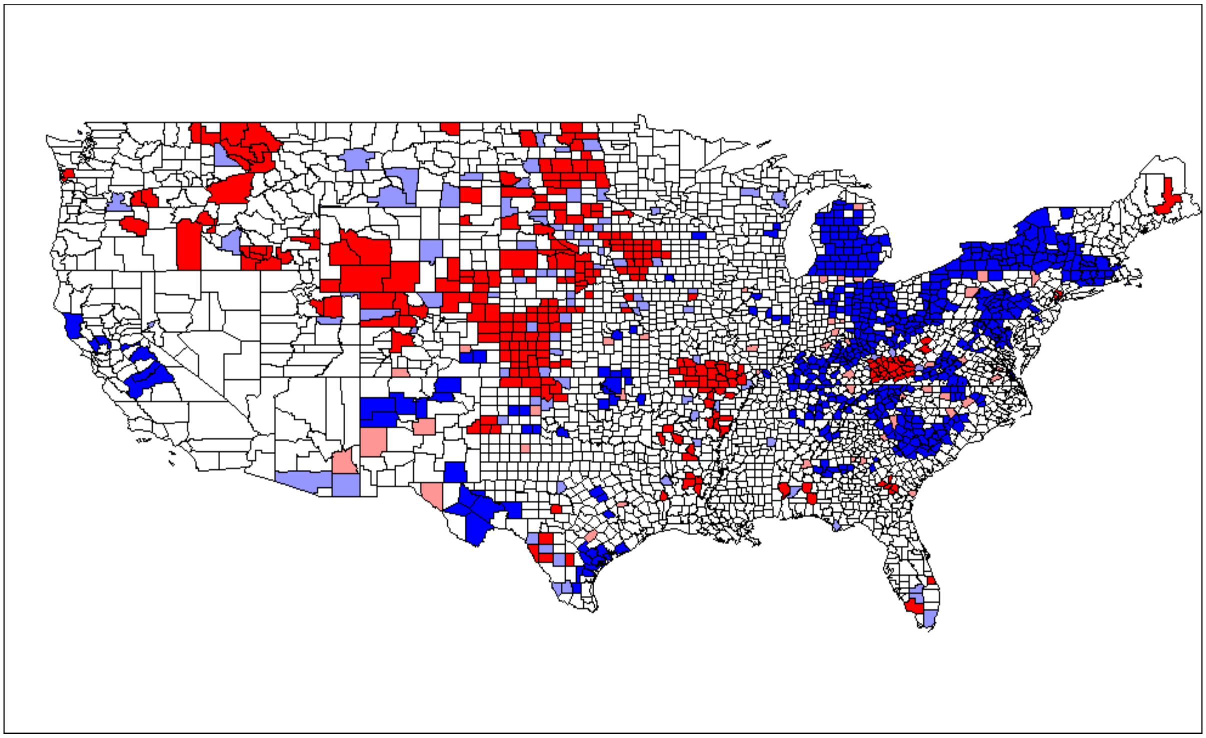


Figure 27: LISA Cluster Map of Distributive Industries (Moran's I = 0.34, p < 0.01)