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SHARES OF EMPLOYMENT IN THE KNOWLEDGE SECTOR AMONG METROPOLITAN AREA ECONOMIES

TIMOTHY P. YUSKAVAGE
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Reviewed and approved* by the following:

Rod Erickson
Professor of Geography and Business Administration
Thesis Supervisor

Ed Coulson
Professor of Economics
Thesis Supervisor

Roger Downs
Professor of Geography
Honors Adviser

* Signatures are on file in the Schreyer Honors College.

Abstract

There is a long of investigation into the nature of clustering among certain industries and certain locations going back to at least to Marshall and other. However, as the modern economy continues to shift from an industrial-based economy to a service-based economy, many previously-held conventions on urban clustering are being reexamined. This paper seeks to better explain why highly skilled ‘knowledge workers’ settle where they do and tries to explain why certain cities become hubs of innovation and growth while others fail to attract the stock of human capital necessary to achieve those gains. The bulk of analysis in this paper will utilize a linear regression between the share of employment in the knowledge sector of metropolitan areas against selected characteristics of the metropolitan areas that we believe will have a significant impact. The majority of data will come from the Census Bureau and will cover all of the Metropolitan Statistical Areas among the fifty states of the U.S. The output will show that isolating specific variables and their impacts is difficult because of the inherent tendency for some of the data to have interaction others. The output, however, will show a slight trend that larger, denser cities tend to have the higher rates of knowledge-sector employment among workers.

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Introduction

The end result, in the minds of many planners, of the many dollars and years spent on local infrastructure such as new sports arenas, improved transportation networks, and ‘business incubators’ is to, in part attract businesses in dynamic fields such as technology, engineering and software. As the share of the American economy in services continues to rise, at the expense of manufacturing and other industrial sectors, cities and regions are showing more and more emphasis on attracting and retaining firms and industries in what some call the “knowledge sector”. What exactly is the knowledge sector? One might think of it as the portion of the service sector which finds that gains in productivity come from workers who are highly-skilled and likely are the recipients of an advanced education. In more simple terms, the sector is made up with people who make their living by primarily utilizing their intellectual talents to perform unique and dynamic services, as opposed to rote repetition of a prescribed task.

Why are these jobs so desirable to mayors and city councils across the country? In today’s increasingly globalized and outsourced world, the division of labor is relatively harsh to those on the bottom relative to those on the top. Hence many industrial occupations, such as low-end manufacturing, are now in condition such that they may be shipped to a low-wage country rather easily. Within our own borders, one needs to look no further than the sluggish economy of the “Rust Belt” region, and then compare that to the more vibrant regional economies of places like Northern Virginia, Silicon Valley, and the Pacific Northwest. In a similar vein, low-end service positions such as retail and hospitality, while large employers in the United States, are not generally the engines for regional economic growth. High-end service jobs on the other hand, such as those in professional or scientific trades, are among the highest-paying jobs in today's economy. This is in no small part due to the significant increases in human capital one gains while receiving an advanced education. Beyond the benefit to the individual, communities also gain from the presence of skilled and highly-educated workers, as will be shown later on in greater detail. Hence, it is clear that in most cases, cities that are aiming for strong and sustained growth would spend their time trying to court these individuals and the businesses that employ them.

The question then is where are the cities which have high rates of employment in the knowledge sector. This thesis will look to answer the question of what cities have created jobs in the knowledge economy at a relatively high rate, and try to explain what are the factors are in those jobs being located there. The thesis will address issues such as urban agglomerations in certain industries, as well as evaluating some of the strategies that cities take to attract an educated workforce.

Ultimately this thesis will offer a model of employment in the knowledge sector, having used regression analysis to analyze data from various cities. The regression will look at a selection of variables, available on a national basis, which is thought to affect the makeup of regional employment. In terms of geography, the model will address the features of every Metropolitan Statistical Areas (MSA) that existed at the time of the 2000 Census, with the exception of four from Puerto Rico. The MSA in Puerto Rico are excluded because of their unique political situation and the dearth of available data in some cases. The relevance of research along these lines is to better understand how local economies form and grow the way that they do. By better understanding this, one can assume that local politicians and planners can have a better understand of what, if anything at all, they can do to achieve their desired local employment profile.

Background

Observing industries at the local level, as opposed to looking at national-level aggregates, through the lens of clustering and agglomeration is hardly a new phenomenon. At least as far back as the late 19^{th} century, Alfred Marshall observed the benefits of business clusters with respect to productivity and innovation. These “agglomeration economies”, Marshall argues, have three main sources: knowledge spillovers, input sharing, and pooling of specialized labor (Marshall, 1890). For each of these sources, there is a benefit that exists only in the event of clustering, at least in the case of specialized industries. First, knowledge spillovers are explained to be an intangible benefit which arises from multiple firms performing similar tasks and gradually adopting one another’s production strategies to increase efficiency. As Marshall in his 1890 book *Principles of Economics*, eloquently puts it, “The mysteries of the trade become no mysteries, but as it were in the air”, as people from different companies interact and invariably share information. Secondly, input sharing allows multiple firms to in the same industries to acquire the necessary parts from the same suppliers, which keeps the overall cost of doing business lower for all of the firms, as opposed to each firm have its own dedicated supplier. A good example is the automobile industry in Detroit, where the “Big Three” automakers draw on the same suppliers for their parts. Thirdly, like input sharing, labor pooling allows employers to draw upon a steady supply of workers, which ensures that their human capital demands will be met. Around the same time, Alfred Weber was also investigating the nature of clustering and agglomeration.

More recently, Krugman formalizes much of what Marshall had suggested at with a model of agglomeration in industry. Empirically, he shows that there is a trend in most industries towards convergence in certain areas, for really most of the reasons that Marshall claimed. Firms, he argue, will aim to minimize their transportation costs by locating either near the source of demand (think automobile parts suppliers in Detroit) or near the source of their inputs (think Pittsburgh's steel mills), which are both in the effort to reduce transportation costs (Krugman, 1991).

In the case of Marshall, Krugman, and much of the work done on this topic, the focal point had largely been industrial organization for firms producing durable goods, such as mining and manufacturing. This much makes sense, for as we go back in time, the share of employment in agriculture and industry was substantially higher than it is today in the industrial world. However, now partly in result of increased productivity and the option to employ cheaper overseas labor, most developed countries over the last few decades have been witnessing a steady increase in the share of employment in the service sector at the expense of the industrial and agricultural sectors. In this context, some of the previous work on industrial agglomeration loses its currency. It is easy to measure, for example, input and output of manufacturing or processing firms. One might ask how many workers are being employed, how many tons of input X are being used and how much output Y the plant produces every month, all of which any manufacturing company would have statistics on.

The same cannot necessarily be said for certain portions of the services sector. How exactly, for example, does one measure the output of a teacher? In the real world, this is proving to be one of the hottest issues in domestic politics. But the problem arises from the fact that we do not really know the best way to measure what the teachers are actually doing. Is it best to utilize graduation rates, or test scores, or experience to measure the quality and/or quantity of a teacher's work? This phenomenon replicates itself countless times in what will be called in this thesis the "knowledge sector" of the economy. A more formal definition will be introduced later, but how does this specific sector compare to the other sectors of the economy? Malmberg, Sölvell, and Zander argue that while agglomeration in the context of Marshall and Krugman's work occurs in order to achieve efficiency and flexibility in transactions, that knowledge sector agglomeration takes place solely for the purpose of information accumulation (Malmberg, 1996). Glaesar and Carlino both state that in the modern economy, large cities, especially those with highly educated populaces are the leading locations of innovation and economic growth, suggesting agglomeration in the knowledge sector (Glaeser, 2003; Carlino, 2001).

Methodology

As stated, this thesis will investigate the role of various factors in the makeup of local economies, specifically as they pertain to employment in the knowledge sector. The first question to answer is what exactly constitutes a knowledge worker in the first place. After all, occupations that we consider "low-skilled" still require at least a marginal amount of mental capacity, even for the most mundane, rote, and repetitive tasks. Although much economic literature focuses on the distinction between the industrial and service sectors, that is not enough in this case. For within the service sector, there is a variety of tasks ranging from hedge fund management and theoretical physics all the way to bartending and retail clerking. This obviously means that the entire service cannot be looked at as a homogenous group, and standards must be set in order to define a knowledge-sector worker. In his paper, Tomlinson examines this very issue of how we define a knowledge worker, and if there are any trends across the board in knowledge-sector employment. In it, he used a large set of survey results of employees to work backwards to determine what constituted a knowledge-sector occupation, including questions such as whether or not their job required constant learning, how long their training periods took place before they could start working productively, and how much technology impacted their jobs on a daily basis. Tomlinson comes to the conclusion that the knowledge sector is largely comprised of occupations which are managerial, scientific and professional in nature (Tomlinson, 1999). Although Tomlinson uses the United Kingdom as the subject for his research, the similarities between the British and American economies are strong enough that we can use his findings for our paper. For our purposes, our statistic of knowledge-sector employment was comprised exclusively from a portion of the P.50 statistics of the SF-3 dataset of the 2000 Decennial Census titled "Management, Professional, and Related Occupations". We found that this subcategory of employment did the best job representing the conclusions of Tomlinson and others in classifying knowledge-sector employment. Note that while management and scientific jobs are probably self-evident, the nature of 'professional' jobs is not as clear. Ultimately it appears that it was something of a judgment call on the part of the Census Bureau.

As stated, the analysis within this thesis will center on regression analysis. Geographically, the scope will be Metropolitan Statistical Areas (MSA) in the United States as defined by the Office of Management and Budget from 2000. There have been changes in the MSA definitions between 2000 and the present. In the event where Consolidated Metropolitan Statistical Areas exist, those will be used in lieu of their constituent MSA. As stated, we will exclude MSA from Puerto Rico because it is not a U.S. state, leaving us with a population of 276 MSA. One important assumption throughout this process is that the MSA is internally homogenous insofar as we will treat the MSA as a single unit without variation within its borders. This, of course, ignores a vast literature which conclusively points out that most metropolitan areas are *not* homogenous units but in fact show great variety depending on location within the area. Nonetheless, for the purposes of this paper, we must restrict our analysis in this way. Future research, however, can and should respect the internal diversity of cities and metropolitan areas.

In terms of the time period, The 2000 Decennial Census and the 2000 County Business Patterns dataset, both from the U.S. Census Bureau, will provide most of the data. (U.S. Census Bureau, 2000a, 2000b). While it would have been preferable to use data from the recently-concluded 2010 Census, giving a more current outlook of the various regional economics, not all of the 2010 data are available at the time of writing this paper. The choice to use every MSA arose from the fact agglomeration literature focuses on clustering in cities, so it would make sense to use every major metropolitan area in the United States as a focal point. The limited sources of data arises from the fact that outside of a few federal statistical agencies, like the Census Bureau and the Bureau of Labor Statistics, there are no datasets which cover every single MSA, and even those that do cover metropolitan areas do not necessarily follow the same standards as the federal agencies do.

Our variable worth explaining is the share of employment in the knowledge sector in MSA. For this paper, it is defined as the aggregate count of employees in the classification of "Management, Professional, and Related Occupations" divided by the total amount of employed people in the MSA. Beginning with this statistic, there is quick insight as to where the regions are that have relatively high shares of knowledge-sector employment. To do this, the location quotient is used to see which MSA are above the national average. The location quotient is generically defined as:

$$\frac{\frac{Regional\ Employment\ in\ Sector\ i}{Regional\ Total\ Employment}}{\frac{National\ Emplyoment\ in\ Sector\ i}{National\ Total\ Employment}}$$

Thus any region with a location quotient greater than 1 has a higher share of employment in a sector than the national share in that same sector. Figures 1, 2, and 3 provide maps of such cities, along with a corresponding table (Table 1) in the appendix. This gives a simple geographic overview of where in the United States the cities are that have the highest shares of knowledge-sector employment.

Model

Our semi-log, ordinary least squares model will follow the generic form:

$y_i = \alpha + \beta x_i + \ln\beta z_i + \gamma D_i + \varepsilon$

Where y_i represents the share of employment in Metropolitan Statistical Area (MSA) *i*, x_i represents variables expressed in terms of percentage of total population in MSA *i*, z_i represents absolute numbers in MSA *i* and D_i represents binary variables in MSA *i*. Our model will employ 22 variables, although several of those are binary variables relating to the same topic.

Regression Variables

This is an overview of the variables used in the regression, simply stating how they were formulated and where they came from. Further explanation of the significances of the variables and why they were included will be located in the discussion of the regression output. Unless otherwise noted, all demographic data comes from the 2000 Census SF-1 and SF-3 datasets.

Knowledge Employment

As explained, this variable is computed by dividing the total amount of workers in the knowledge sector (previously defined) by the total amount of workers in the MSA. This will be our dependent variables in the model.

Population

This is the total population for each MSA. The model will use the natural log of population. Our hypothesis would expect a fairly strong relationship between population and knowledge-sector employment, based off of the ideas behind agglomeration benefits.

Population Growth Rate

This is measured as the percentage change in the population of a given MSA between the 1990 and 2000 Census. It is worth noting that between the two censuses, the definitions of several MSAs changed. Because this statistic is taken directly from the Census Bureau however, it is assumed that the statistic has already accounted for these changes. We would anticipate a positive relationship, but for different reasons than absolute population; fast-growing areas tend to do so because of a dynamic and vibrant economy. The driver of economic growth during the period of 1990-2000 was the technology sector, which would heavily overlap the class of knowledge workers.

Race

This statistic is derived by taking the proportion of non-Hispanic white and Asians for every MSA. Census Bureau analysis has shown that non-Hispanic whites and Asians consistently higher educational attainment levels than other races and ethnicities, and those skills are largely required in order to participate in the skilled-sector labor market, so our prediction would be that of a positive relationship (Census Bureau, 2004).

Native

This is the percent of the population of each MSA which was born in the United States. It really is not clear what this statistic will reveal, as the two large sets of immigrants into the United States are either on the rather low end, such as food service, construction or janitorial work, or the very high end, such as doctors and technology workers.

Local

This is the percent of the population of the MSA in 2000 that was living in the same MSA in 1995. This was derived by taking the total amount of people in 2000 living in the same house in 1995, or a different house but the same MSA in 1995, and dividing it by the total 2000 MSA population. Similar to population growth, a high value for this statistic would suggest a stagnant population, and perhaps a static economy.

Commute

This variable expresses the average commute time per commuter in an MSA and also serves as a general indicator of traffic congestion. This was computed by taking the aggregate amount of commuting minutes for each MSA, and then dividing it by the total population. Our hypothesis for this statistic is not clear, as longer commute times is a type of 'negative amenity' that would drive away prospective employees, but the most vibrant areas are likely to have worse congestion as a result of an influx of workers that the local transportation capacity cannot handle.

Aviation

This statistic shows the number of enplanements (passengers boarding a commercial airliner) per 100,000 residents among all of the airports in a given MSA in 2001. Therefore a higher statistic shows a busier airport relative to the size of the MSA population. The larger airports will probably not reveal much, and hence this statistic on the high-end might be largely correlated with MSA population. On the medium-to-small scale, however, there is the distinct possibility that a smaller MSA with a disproportionally busy airport is capable of handling more business than a comparable MSA, allowing is to take in a higher degree of skilled businesses. The data comes from an FAA dataset (FAA, 2001).

Heating Degree Days

This is a measurement of the annual amount of Heating Degree Days in each MSA, which is a rough way of showing the annual "coldness" of a given MSA. For the regression we will take the log of Heating Degree days. Our source is NOAA climatic data (National Oceanographic and Atmospheric Administration, 2004). There will be further analysis of this topic later in the thesis, but for now the prediction is of a negative relationship, as sectors such as tourism and hospitality are much more contingent on warm-weather than knowledge-sector industries are.

Culture

This is a measurement of the amount of cultural institutions per 100,000 people in each MSA. We computed this by taking the total count of establishments in each MSA under the NAICS codes of 7111, which is "Performing Arts Companies", 7112, which is

"Spectator Sports", and 712, which is "Museums, Historical Sites, and Similar Institutions". For the regression we will take the log of culture. Some may argue that this variable is susceptible to endogeneity, as educated people would naturally demand a vast array of cultural amenities to improve their living standards, but it is worth noting that this statistic does not cover just 'highbrow' institutions, but also spectator sports.

Knowledge Firms

This statistic measures the amount of knowledge firms (as opposed to employees) per 100,000 people in each MSA. The industries used to determine this statistic were drawn heavily from Tomlinson's definition of the knowledge economy. Table 2 in the appendix shows the industries included in this statistic. For reasons that should be obvious, we hypothesize a strong and positive relationship between these two variables, although the statistic says nothing about the nature of the firms themselves, such as size or annual output.

Poverty

This is measured as the total population per MSA of people who reported poverty status divided by the total population of the MSA. Given the constraints on local-level data, this is a simple, albeit incomplete way of at least addressing income distribution within the MSA. One would expect low poverty in areas with high rates of skilled employment.

Rents

This is measured as the median gross rent for every MSA. The model will use the natural log of rents. Besides acting as an incentive (or disincentive) for a knowledge-sector employee to relocate to an MSA, it gives us an idea of the relative cost-of-living from MSA to MSA.

Population Density

This is given directly by the Census Bureau, from the Housing Census of 2000. The model will use the natural log of population density. This will test if agglomeration occurs at a very literal level, that is, if people are literally living closer to one another, will that result in more collaborative efforts and hence increase the rate of employment in the skilled-sector.

Regional Binary Variables

The first binary variable, 'Region' defines the location of each MSA in terms of one of nine national regions as defined by the Census Bureau. See Figure 4 in the appendix for a reference map.

The second binary variable, 'Coastline', shows whether or not the MSA is located in a state which borders either the Atlantic or Pacific Ocean. Both of these are testing for preferences among people when choosing to locate to one area or another. Holding all else constant, one would expect coastal areas and regions to be positively linked because of the large agglomerative regional economies already established there.

Regression Output

Variable	Coefficient	Std Error	t-value	p-value
Population	.0096	.0045	2.14	.034
Pop. Growth	-.0392	.0289	-1.35	.177
Race	-.0482	.0304	-1.58	.115
Native	.0537	.0695	0.77	.441
Local	.3519	.0483	7.29	.000
Commute	.0016	.0012	1.34	.182
Aviation	-.0006	.0017	-0.37	.712
HDD	$7.22*10^{-6}$	$1.95*10^{-6}$	3.69	.000
Culture	.0001	.0008	0.05	.963
Skilled Firms	.0001	.0000	4.39	.000
Poverty	.2375	.0783	0.30	.762
Rents	-.1235	.0064	-1.93	.055
Density	.0129	.0052	2.49	.014
Region 2	.0011	.0173	0.06	.949
Region 3	-.0077	.0192	-0.40	.688
Region 4	.0069	.0197	0.35	.727
Region 5	-.0085	.0175	-0.49	.627
Region 6	.0068	.0212	0.02	.984
Region 7	.0004	.0212	0.02	.984
Region 8	-.0051	.0222	-0.23	.819
Region 9	-.012	.0185	-0.66	.513
Coastal	-.0020	.0113	-0.18	.860
Constant	.0705	.1193	0.59	.556

Notes: Adj R^2 = .4261; Region 1 dropped from regression as it is implied through the results of Regions 2-9

Regression Analysis

Looking at the output, the non-binary variables are about evenly divided between statistically significant and not statistically significant. For the geographic binary variables, none of them are statistically significant, and none are even close to being significant.

Population

Carlino shows that innovation in cities is closely linked to total employment in a city (Carlino, 2005). That is, absolutely larger totals of employment would result in increased levels of innovation, regardless of the makeup of the employed. Although population does not perfectly mirror total employment, as it does not control for labor force participation or unemployment rates, it would make sense to expect the two statistics to mirror each other fairly well. The output shows a clear and rather strong link between population and employment in this sector. And recalling earlier in the thesis where the link between rates of skilled-employment and innovation was discussed, Carlino's findings seem to validate this coefficient quite well.

Population Growth

The effect of population growth runs contrary to both the prediction in the previous section and the like of Glaeser and Saiz, who document the sharp relationship between population growth and human capital stock in cities (2003). This may be replicating some of the effect of the 'native' statistic that will be addressed later in this section; because population growth accounts for natural population growth, domestic migration and immigration, and since there is no way of knowing the breakdown for each MSA, there is not much to be done with this statistic.

Race

The result on this variable was surprising because of the long-standing literature documenting the significant gap in educational attainment between whites and Asians, and the rest of society. Part of this may be due to ‘error’ in how respondents identify themselves for the Census, but that is nothing more than speculation.

Native

This statistic can be used as a general proxy of immigration for each MSA, and there are two key factors at work behind it. The first is of immigrants who come to the United States to perform low-skilled labor, such as farm harvesting or food service. The other is immigrants who come to the United States on skilled worker visas to meet a niche demand for skilled labor. Thus there are two effects working against one another. Looking at the output, it appears that the unskilled labor effect outweighs the skilled labor effect of immigration, although there is a low significance level.

Local

This represents the rate of migration into regions including domestic relocation. We anticipated a negative relationship, since people will tend to move into places with more dynamic economic outlooks, and that the stronger engines for growth in today’s economy are currently cities with high rates of innovation and knowledge-sector growth.

As it turns out there is a negative relationship, but it is not very large. Because this variable includes both immigration and domestic migration, the relatively large rate of immigration into the United States may be flooding the results a bit, which is why our output tends to be similar to the native/non-native category.

Commute

There are many ways to look into this result, but it is important to remember that it is not statistically significant. A basic monocentric city model will suggest that higher-earning people would live further from their jobs because they could afford the costs. Furthermore, even if there is not the assumption of a monocentric model, there is the chance that suburban office parks and research parks are the culprit behind increased commute times, as employees are forced to drive to work from suburb to suburb.

Aviation

This weak negative relationship was not helped by the fact that data was not readily available for some of the smaller MSA. Certainly airport volume rates will be tied with local population, but there is also the consideration about airport hubs which may or may not have anything to do with the locality besides airport user fees. That is, there might be a busy airport relative to the size of the local MSA, but that does not at all necessarily imply a greater-than-average flow of people coming or going on business meetings at that MSA. Rather, the increased flight load may simply be because it is a cheap airport to have as a hub, and the high enplanement rates are from transfers who never leave the airport. This is unlikely at the very smallest airports, but the possibility is greater at medium-sized ones.

Heating Degree Days

A Heating Degree Day is a statistic to measure energy demand for heating. It is measured by taking the difference between an already selected temperature, usually room temperature, and the average outdoor temperature. This process is repeated every day, so if on day 1, the temperature was 5 degrees below the baseline temperature, and then on day 2, the temperature was 7 degrees below, and then there would be 12 Heating Degree Days over the course of two days. Hence, the larger the count, the more total degrees a place has been the whole year, giving as a good measure of yearly 'coldness'.

The results seem to indicate that weather, at least temperature, is not a crucial deciding factor when it comes to where knowledge employees are located. One factor is that while warm-weather climates will attract knowledge employees, they will attract everyone else too, and according to the data, at higher rates. And as Glaeser notes, many cities in the north have redefined themselves as technological hubs out of necessity. He specifically cites Minneapolis and Boston (both are in the top thirty for rate of knowledge employment) as examples of cold-weather cities that have reinvented themselves and staved off some population decline (Glaeser, 2005). In a way, coldness, at least in big cities, may prove to be an unexpected positive incentive, as it perhaps forces the cities to focus their energies on attracting the most stable growth industries, which are currently those in the professional and scientific mold.

Culture

This variable serves as an attempt to test Richard Florida's popular thesis on what it takes to attract talented workers. In his various papers and lectures, he has expressed a rule-of-thumb that cities need creative, innovative people to foster and drive city growth. The question for city planners is what they must do to successfully bring those people to their respective cities. Part of the solution, Florida states, is to create "Bohemian"-type cities which are hospitable to the young, artistic, and creative (Florida, 2002). This is why Cleveland (Rock and Roll Hall of Fame), Philadelphia (Kimmel Center) and countless other metro areas have either underwritten museums, or sponsored 'art districts' to attract and retain these types of workers. Our coefficient for cultural institutions, which covers arts, music, sports, museums and similar establishments, shows a non-significant weak relationship between cultural venues and employment in the knowledge economy. This should not be interpreted as an indictment against any arguments coming from the 'creative class' school of thought, as this statistic merely shows brick-and-mortar businesses and does not begin to address intangible factors such as the local zeitgeist. Moreover, this statistic does not perfectly reflect Florida's own metrics and indices, so it would not be fair to compare the results directly. This approach simply attempts to see if there is a general relationship between the two categories, using the data which happens to be available.

Knowledge Firms

There is almost no relationship between the presence of firms in the knowledge sector and the rate of employment of people who work there. It goes without saying that firms in the sector of the economy that work with knowledgeable topics are going to need knowledgeable people to do that work. Yet a 1% increase in the amount of firms has as 0.07% increase in the amount of knowledge workers. Like the cultural statistic, this may simply be a reflection that the variable was not well put-together.

On the other hand, this may be a result of the principle behind the base multiplier: the industries where people in the knowledge-sector work will usually be “export” goods for many cities, such as engineering or software. Hence adding one employer in that primary field may result in several employers in tertiary sectors, feeding off the regional multiplier effect.

Poverty

Poverty and employment are strongly related but not at a significant level. The initial reaction on this result was one relating a spatial mismatch issue, whereby as cities that are high in knowledge-sector employment will not be able to employ low-skilled people as well, combined with a possible price increase associated with the increased rate of high-productivity, high-wage workers.

Rents

The rent value shows at a nearly significant level that the percentage of highly-educated people in an MSA goes down when the rents go up. There is undoubtedly an income effect in this picture, but one has to wonder who is moving in if the most productive and presumably higher-salaried people are moving out. There is the possibility that high rents leads to people moving outside of the MSA to avoid high prices or taxes and then commuting, but that is hard to tell, as the geographic extent of MSA tend to cover all of the surrounding suburbs and then some more area beyond that.

Density

The strong positive relationship with statistical significance seems to justify those who connect population density with urban innovation. That said, what would really matter in this case is not so much the density of living arrangements, but *working* arrangements, if we are to believe the premise behind the spillover effects. There is a very strong degree of correlation between population and population density, so there is also probably a redundancy of the effect of population in this variable.

Region/Coastline

William Nordhaus gets to the point when he says that "The linkage between economic activity and geography is obvious: Populations cluster mainly on coasts and rarely on ice sheets" (Nordhaus, 2005), but our test results do not suggest that. The issue with these statistics is how well the various regions and coastal designations really represent the locations of the various MSA. For instance, West Virginia and Florida are part of the same region, but there is very little in common between the two states. In the western United States, the regions cover such a large area that they start to lose their meaning when it comes to localized effects on MSA. The coastline test fell short for similar reasons. When classifying regions on a state-by-state basis, outside of maybe the small northeastern states, the areas involved are just too big, and you lose whatever unique local effects were present on the data.

Constant

Our constant is not statistically significant, and does not have any intrinsic value unto itself.

Comments

This model is by no means perfect. Perhaps the biggest obstacle to addressing the question at a deeper level is the lack of necessary data. The nature of this project requires standardized nationwide data at the Metropolitan Statistical Area level, which invariably is only provided by the federal government. While these resources served as the basis of the model, there are many data which for various reasons the federal government cannot collect, while the local and state governments could do much better. However the issue of standardization comes up, as there are no guarantees that data are consistent across jurisdictional lines, requiring the migration back to federal data sources.

Some of the statistics, like the ones measuring cultural institutions, airline traffic and knowledge-sector firms, were derived for this paper and thus are ultimately subjective to one degree or another. There is a distinct possibility that there are better ways to quantify the things that this model was trying to do. That said, it does not appear that endogeneity is an inherent issue in the model, as the R^2 value, in the mid-40s, is not excessively high.

If anything, the thesis and model also shows why answering the question of "what attracts smart people to a city" still does not have a totally definitive answer. Unlike manufacturing, where plants are large have high fixed costs, or mineral industries, which draw upon immovable natural resources, knowledge-sector work is relatively mobile. While there will always be fixed demand for lawyers and doctors in every city, the inputs of those industries, the doctors and lawyers, can always move freely to another city with the purchase of a plane ticket. The nature of the work of knowledge-sector workers also makes it difficult to even quantify what they do. How does one measure the output of a teacher, or a consultant, or an architect? These occupations employ intangible assets, namely intelligence, and many have outputs of and intangible nature.

There certainly are follow-up opportunities to build upon this initial research. Currently, data from the 2010 is only available on a very small-scale basis. This means that for one, the data used in this thesis are dated to fairly significant extent, especially when thought of in context of all of the economic change which happened in the high-technology sector over the last decade. Additionally, this hindrance prevented time-series analysis, as any models would have to go back to 1990, and given all of the changes which happened between then and now, in the field of high-technology industries, there might not be any clear conclusions from such an analysis. When these data are available a few years down the road, someone could repeat this experiment with the same datasets, just updated data, and get different results.

Conclusion

Like most research and many experiments, this thesis answered some questions and has prompted some new questions to be answered. If this were to be done again or be further revised, there would be a push to get better input variables, particularly the ones personally derived for this paper. One facet of that would be a search for datasets which provide data that are more representative of the trends and patterns that the model tries to incorporate. When comparing the results to the hypotheses, it is better to think about the individual predictions given to each variable before running the regression rather than one over-arching hypothesis, as this was a totally new interaction of variables and hence there was very little to go by in terms of a precedent.

Is there anything to take away from this? The first is that there are still more questions than answers. But it more intriguing than some of the relationships that showed up was the *lack* of relationships; little-to-no effect by commuting times, airport access, warm weather, or proximity to ocean fronts. The low significance levels of many of the variables suggests there are factors that are just unquantifiable at this point for one reason or another, such as quality of local governance, quality-of-life, the local culture, ethos, or zeitgeist.

In sum, there are many parts of this model which have not answered our questions, either because of the quality of the data or the nature of the relationship between our dependent variable and certain independent variables. These shortcomings should allow room for future improvement as the author's econometric skills and a wider range of data become available.

Appendix

Table 1- Metropolitan Statistical Areas by Location Quotient

MSA	LQ
Danville, VA MSA	0.638628
Hickory--Morganton--Lenoir, NC MSA	0.65921
Steubenville--Weirton, OH--WV MSA	0.668802
Mansfield, OH MSA	0.693938
Elkhart--Goshen, IN MSA	0.706377
Las Vegas, NV--AZ MSA	0.713755
Williamsport, PA MSA	0.725656
Sumter, SC MSA	0.740218
Youngstown--Warren, OH MSA	0.740659
Fort Smith, AR--OK MSA	0.743608
Decatur, AL MSA	0.744974
Houma, LA MSA	0.748417
Gadsden, AL MSA	0.750582
Visalia--Tulare--Porterville, CA MSA	0.751187
Janesville--Beloit, WI MSA	0.754661
Florence, AL MSA	0.755288
Lima, OH MSA	0.756167
Anniston, AL MSA	0.757117
Altoona, PA MSA	0.76031
Merced, CA MSA	0.760964
Rocky Mount, NC MSA	0.76189
Cumberland, MD--WV MSA	0.764145
Kokomo, IN MSA	0.770908
Sheboygan, WI MSA	0.770939
Joplin, MO MSA	0.771018
Jacksonville, NC MSA	0.774487
Lewiston--Auburn, ME MSA	0.775916
Myrtle Beach, SC MSA	0.778466
Lakeland--Winter Haven, FL MSA	0.779512
McAllen--Edinburg--Mission, TX MSA	0.78095
Yuba City, CA MSA	0.782447
Ocala, FL MSA	0.783798
Modesto, CA MSA	0.787346
Clarksville--Hopkinsville, TN--KY MSA	0.791964
Yuma, AZ MSA	0.792647
Laredo, TX MSA	0.794971
Johnstown, PA MSA	0.795902

Bakersfield, CA MSA	0.801637
Sioux City, IA--NE MSA	0.803459
Wheeling, WV--OH MSA	0.805809
Stockton--Lodi, CA MSA	0.806085
Punta Gorda, FL MSA	0.807017
Johnson City--Kingsport--Bristol, TN--VA MSA	0.807368
Lake Charles, LA MSA	0.807995
Jamestown, NY MSA	0.808222
Pine Bluff, AR MSA	0.808508
Huntington--Ashland, WV--KY--OH MSA	0.809028
Texarkana, TX--Texarkana, AR MSA	0.809139
Enid, OK MSA	0.809746
Longview--Marshall, TX MSA	0.813281
Yakima, WA MSA	0.814138
Beaumont--Port Arthur, TX MSA	0.816119
Terre Haute, IN MSA	0.816675
Jackson, MI MSA	0.816695
Sharon, PA MSA	0.82034
Brownsville--Harlingen--San Benito, TX MSA	0.821945
Biloxi--Gulfport--Pascagoula, MS MSA	0.823005
Dothan, AL MSA	0.824282
St. Joseph, MO MSA	0.826921
San Angelo, TX MSA	0.828057
Scranton--Wilkes-Barre--Hazleton, PA MSA	0.828109
Owensboro, KY MSA	0.834256
Goldsboro, NC MSA	0.834565
Lancaster, PA MSA	0.835687
Canton--Massillon, OH MSA	0.836327
Fort Myers--Cape Coral, FL MSA	0.836379
Pueblo, CO MSA	0.838941
Parkersburg--Marietta, WV--OH MSA	0.839612
Fort Pierce--Port St. Lucie, FL MSA	0.840555
Evansville--Henderson, IN--KY MSA	0.842017
York, PA MSA	0.8434
Naples, FL MSA	0.844273
Decatur, IL MSA	0.845378
Jonesboro, AR MSA	0.845658
Casper, WY MSA	0.845995
Panama City, FL MSA	0.847196
Dover, DE MSA	0.84786
Victoria, TX MSA	0.84826

Shreveport--Bossier City, LA MSA	0.850433
Glens Falls, NY MSA	0.855531
Lynchburg, VA MSA	0.855648
Fayetteville, NC MSA	0.857277
Daytona Beach, FL MSA	0.857978
Fort Wayne, IN MSA	0.858011
Fresno, CA MSA	0.858373
Rockford, IL MSA	0.861461
Greenville--Spartanburg--Anderson, SC MSA	0.861591
Wichita Falls, TX MSA	0.862502
El Paso, TX MSA	0.866327
Mobile, AL MSA	0.866399
Salinas, CA MSA	0.866647
Erie, PA MSA	0.868148
St. Cloud, MN MSA	0.869522
Benton Harbor, MI MSA	0.87019
Reading, PA MSA	0.870932
Grand Junction, CO MSA	0.871819
Saginaw--Bay City--Midland, MI MSA	0.872548
Springfield, MO MSA	0.873014
Davenport--Moline--Rock Island, IA--IL MSA	0.873648
Columbus, GA--AL MSA	0.874552
Odessa--Midland, TX MSA	0.874897
Reno, NV MSA	0.877191
Lawton, OK MSA	0.877379
Amarillo, TX MSA	0.878291
Sherman--Denison, TX MSA	0.879086
Corpus Christi, TX MSA	0.879463
Grand Rapids--Muskegon--Holland, MI MSA	0.880414
Wausau, WI MSA	0.881799
Albany, GA MSA	0.882277
Dubuque, IA MSA	0.883473
Eau Claire, WI MSA	0.884115
Duluth--Superior, MN--WI MSA	0.885061
Jackson, TN MSA	0.885193
Appleton--Oshkosh--Neenah, WI MSA	0.886503
Chattanooga, TN--GA MSA	0.888715
Lafayette, LA MSA	0.889384
Waco, TX MSA	0.891851
Killeen--Temple, TX MSA	0.895084
Muncie, IN MSA	0.895519

Toledo, OH MSA	0.896461
Florence, SC MSA	0.897999
Tyler, TX MSA	0.901002
Waterloo--Cedar Falls, IA MSA	0.901656
Redding, CA MSA	0.904744
Sarasota--Bradenton, FL MSA	0.907197
Great Falls, MT MSA	0.907717
Greensboro--Winston-Salem--High Point, NC MSA	0.908265
Green Bay, WI MSA	0.908564
Medford--Ashland, OR MSA	0.90907
Pensacola, FL MSA	0.913005
Fayetteville--Springdale--Rogers, AR MSA	0.9143
Monroe, LA MSA	0.915963
Kalamazoo--Battle Creek, MI MSA	0.920009
Utica--Rome, NY MSA	0.920139
Macon, GA MSA	0.921613
Billings, MT MSA	0.922491
Hattiesburg, MS MSA	0.924388
Sioux Falls, SD MSA	0.924624
Louisville, KY--IN MSA	0.926782
Savannah, GA MSA	0.927466
La Crosse, WI--MN MSA	0.928725
Wilmington, NC MSA	0.931108
Alexandria, LA MSA	0.933006
Bellingham, WA MSA	0.93626
Miami--Fort Lauderdale, FL CMSA	0.939164
Grand Forks, ND--MN MSA	0.940091
Chico--Paradise, CA MSA	0.941364
Asheville, NC MSA	0.942457
Memphis, TN--AR--MS MSA	0.942602
Allentown--Bethlehem--Easton, PA MSA	0.942672
Rapid City, SD MSA	0.944846
Roanoke, VA MSA	0.947052
Eugene--Springfield, OR MSA	0.947964
Jacksonville, FL MSA	0.951609
Tuscaloosa, AL MSA	0.951703
Wichita, KS MSA	0.951716
Elmira, NY MSA	0.952096
Fort Walton Beach, FL MSA	0.952451
South Bend, IN MSA	0.952949
Abilene, TX MSA	0.953387

Tulsa, OK MSA	0.956562
Harrisburg--Lebanon--Carlisle, PA MSA	0.957101
Cheyenne, WY MSA	0.957606
Pocatello, ID MSA	0.95856
Missoula, MT MSA	0.958931
Las Cruces, NM MSA	0.959663
Oklahoma City, OK MSA	0.961612
Augusta--Aiken, GA--SC MSA	0.96321
Charleston--North Charleston, SC MSA	0.965546
Knoxville, TN MSA	0.965857
Orlando, FL MSA	0.968527
Salt Lake City--Ogden, UT MSA	0.970567
San Antonio, TX MSA	0.972473
Cleveland--Akron, OH CMSA	0.97409
Tampa--St. Petersburg--Clearwater, FL MSA	0.974344
Peoria--Pekin, IL MSA	0.974399
Dayton--Springfield, OH MSA	0.975914
New Orleans, LA MSA	0.976661
Providence--Fall River--Warwick, RI--MA MSA	0.979789
Fargo--Moorhead, ND--MN MSA	0.979945
Spokane, WA MSA	0.980687
Charlotte--Gastonia--Rock Hill, NC--SC MSA	0.980814
Lubbock, TX MSA	0.985304
Baton Rouge, LA MSA	0.986501
Phoenix--Mesa, AZ MSA	0.992511
Charleston, WV MSA	0.993739
Buffalo--Niagara Falls, NY MSA	0.997648
Norfolk--Virginia Beach--Newport News, VA--NC MSA	0.998421
Lafayette, IN MSA	0.999316
Little Rock--North Little Rock, AR MSA	1.001012
Indianapolis, IN MSA	1.002281
Greenville, NC MSA	1.002538
Honolulu, HI MSA	1.004632
Detroit--Ann Arbor--Flint, MI CMSA	1.004856
Montgomery, AL MSA	1.005141
Auburn--Opelika, AL MSA	1.006513
Pittsburgh, PA MSA	1.008166
Cincinnati--Hamilton, OH--KY--IN CMSA	1.008509
Syracuse, NY MSA	1.008592
Los Angeles--Riverside--Orange County, CA CMSA	1.010034
New London--Norwich, CT--RI MSA	1.014024

Topeka, KS MSA	1.016514
San Luis Obispo--Atascadero--Paso Robles, CA MSA	1.018462
West Palm Beach--Boca Raton, FL MSA	1.021209
Birmingham, AL MSA	1.021583
Springfield, MA MSA	1.021716
St. Louis, MO--IL MSA	1.021809
Pittsfield, MA MSA	1.024968
Binghamton, NY MSA	1.025082
Portland--Salem, OR--WA CMSA	1.02582
Flagstaff, AZ--UT MSA	1.02625
Lansing--East Lansing, MI MSA	1.027472
Milwaukee--Racine, WI CMSA	1.027552
Barnstable--Yarmouth, MA MSA	1.029814
Nashville, TN MSA	1.030346
Bangor, ME MSA	1.030428
Cedar Rapids, IA MSA	1.035291
Boise City, ID MSA	1.036011
Richland--Kennewick--Pasco, WA MSA	1.038075
Melbourne--Titusville--Palm Bay, FL MSA	1.038735
Omaha, NE--IA MSA	1.039431
Tucson, AZ MSA	1.039748
Bismarck, ND MSA	1.039873
Jackson, MS MSA	1.044106
Houston--Galveston--Brazoria, TX CMSA	1.045824
Santa Barbara--Santa Maria--Lompoc, CA MSA	1.050792
Lexington, KY MSA	1.055153
Chicago--Gary--Kenosha, IL--IN--WI CMSA	1.055903
Des Moines, IA MSA	1.059481
Athens, GA MSA	1.060005
Kansas City, MO--KS MSA	1.063673
Lincoln, NE MSA	1.06963
Dallas--Fort Worth, TX CMSA	1.070019
Columbus, OH MSA	1.081267
Provo--Orem, UT MSA	1.084217
Albuquerque, NM MSA	1.09323
Anchorage, AK MSA	1.09372
Philadelphia--Wilmington--Atlantic City, PA--NJ--DE--MD CMSA	1.095856
Richmond--Petersburg, VA MSA	1.09854
Rochester, NY MSA	1.102336
Colorado Springs, CO MSA	1.104513

Columbia, SC MSA	1.107846
Bloomington--Normal, IL MSA	1.109097
Sacramento--Yolo, CA CMSA	1.109799
Atlanta, GA MSA	1.114026
San Diego, CA MSA	1.119113
Portland, ME MSA	1.13726
Seattle--Tacoma--Bremerton, WA CMSA	1.142
Albany--Schenectady--Troy, NY MSA	1.145385
New York--Northern New Jersey--Long Island, NY--NJ--CT--PA CMSA	1.147118
Minneapolis--St. Paul, MN--WI MSA	1.157348
Springfield, IL MSA	1.160091
Hartford, CT MSA	1.163056
Bryan--College Station, TX MSA	1.167502
Denver--Boulder--Greeley, CO CMSA	1.170031
Bloomington, IN MSA	1.172376
Fort Collins--Loveland, CO MSA	1.178016
Lawrence, KS MSA	1.20047
Huntsville, AL MSA	1.200548
Burlington, VT MSA	1.234342
State College, PA MSA	1.236715
Columbia, MO MSA	1.241522
Austin--San Marcos, TX MSA	1.245646
Boston--Worcester--Lawrence, MA--NH--ME--CT CMSA	1.250837
Champaign--Urbana, IL MSA	1.255633
Tallahassee, FL MSA	1.271789
Iowa City, IA MSA	1.286567
San Francisco--Oakland--San Jose, CA CMSA	1.294534
Madison, WI MSA	1.296588
Gainesville, FL MSA	1.307717
Raleigh--Durham--Chapel Hill, NC MSA	1.315296
Rochester, MN MSA	1.3212
Santa Fe, NM MSA	1.34191
Charlottesville, VA MSA	1.347941
Washington--Baltimore, DC--MD--VA--WV CMSA	1.349459
Corvallis, OR MSA	1.392978

Source: 2000 County Business Patterns, U.S. Census Bureau

Table 2 – Components of knowledge sector by NAICS code

NAICS Code	Description
51	Information
52	Finance and Insurance
531	Real Estate
54	Professional, Scientific, and Technical Services
55	Management of Companies and Enterprises
61	Educational Services
62	Health Care and Social Assistance
711	Performing Arts, Spectator Sports, and Related Industries

Table 3 – Summary statistics for regression variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Knowledge Employment	276	0.3170248	0.0476808	0.2148759	0.4686881
Population	276	818774.3	1968621	57813	2.12E+07
Native	276	0.9371151	0.0636772	0.5980394	0.991478
New Residents	276	0.1950091	0.0707405	0.0754614	0.4578188
Heating Degree Days	276	4221.094	2231.931	0	9841
Culture	276	6.542736	3.820081	0	34.23526
Knowledge Firms	276	784.4432	187.5938	0	1502.808
Commute	276	21.78293	3.21772	15.0579	34.03267
Poverty	276	0.1257511	0.0462579	0.0502281	0.4343103
Growth	276	0.1356043	0.1217597	-0.0738	0.8333
Race	276	0.7742572	0.1624109	0.052	0.979
Density	276	279.2525	251.3191	5.4	2028.7
Rent	274	91117.15	39775.92	9999	334800
Aviation	213	1.673384	2.02771	0.0164138	11.19762
Region 1	276	0.0398551	0.195974	0	1
Region 2	276	0.0869565	0.2822832	0	1
Region 3	276	0.1557971	0.3633217	0	1
Region 4	276	0.0978261	0.297619	0	1
Region 5	276	0.2028986	0.4028881	0	1
Region 6	276	0.0869565	0.2822832	0	1
Region 7	276	0.1485507	0.3562911	0	1
Region 8	276	0.0833333	0.2768875	0	1
Region 9	276	0.0978261	0.297619	0	1
Coastal	276	0.6304348	0.4835638	0	1
Inland	276	0.3695652	0.4835638	0	1

Figure 1

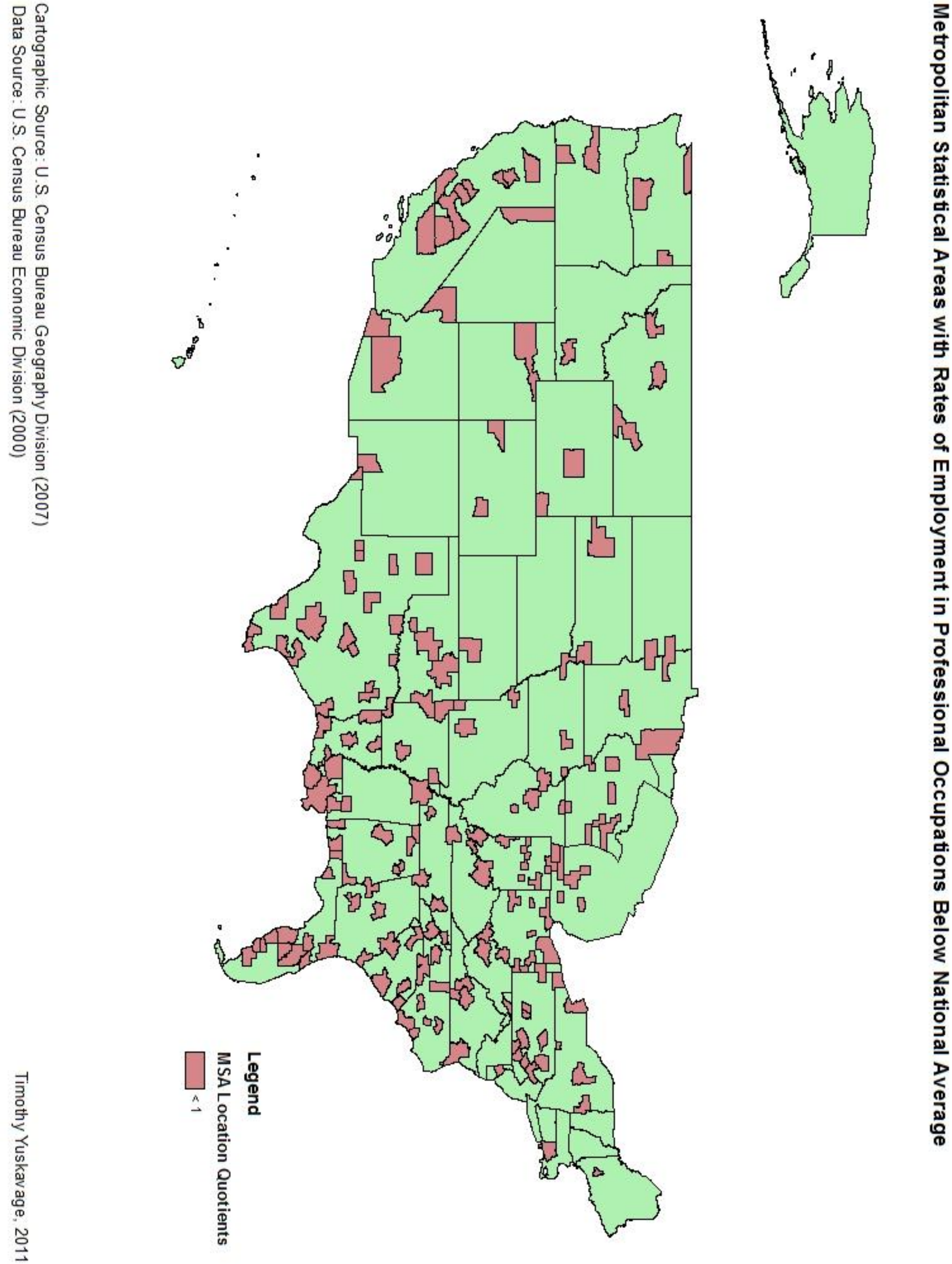
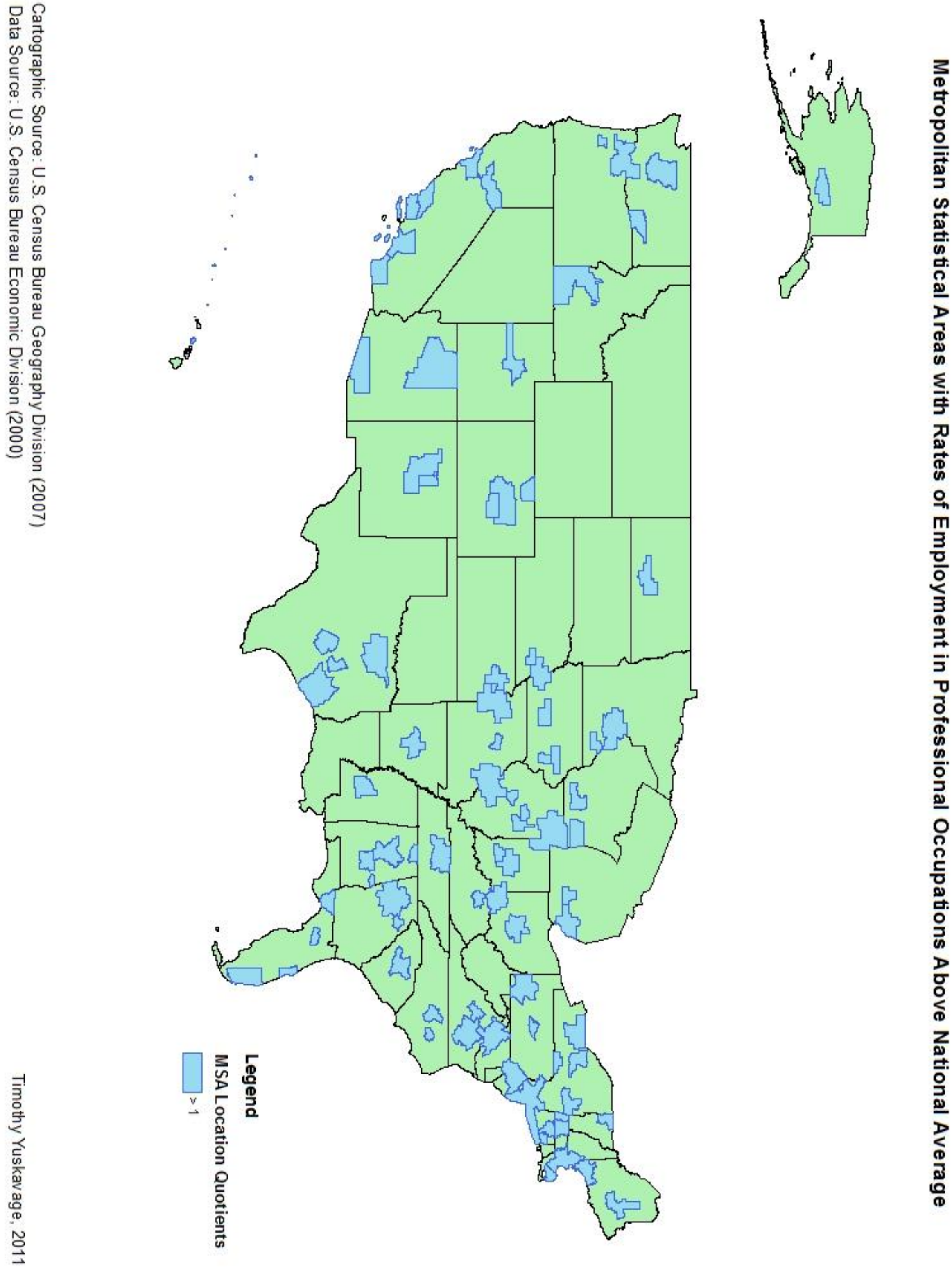

Metropolitan Statistical Areas with Rates of Employment in Professional Occupations Below National Average
Legend
MSA Location Quotients
< 1
Cartographic Source: U.S. Census Bureau Geography Division (2007)
Data Source: U.S. Census Bureau Economic Division (2000)
Timothy Yuskavage, 2011

Figure 2


Metropolitan Statistical Areas with Rates of Employment in Professional Occupations Above National Average
Legend
MSA Location Quotients
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Cartographic Source: U.S. Census Bureau Geography Division (2007)
Data Source: U.S. Census Bureau Economic Division (2000)
Timothy Yuskavage, 2011

Figure 3

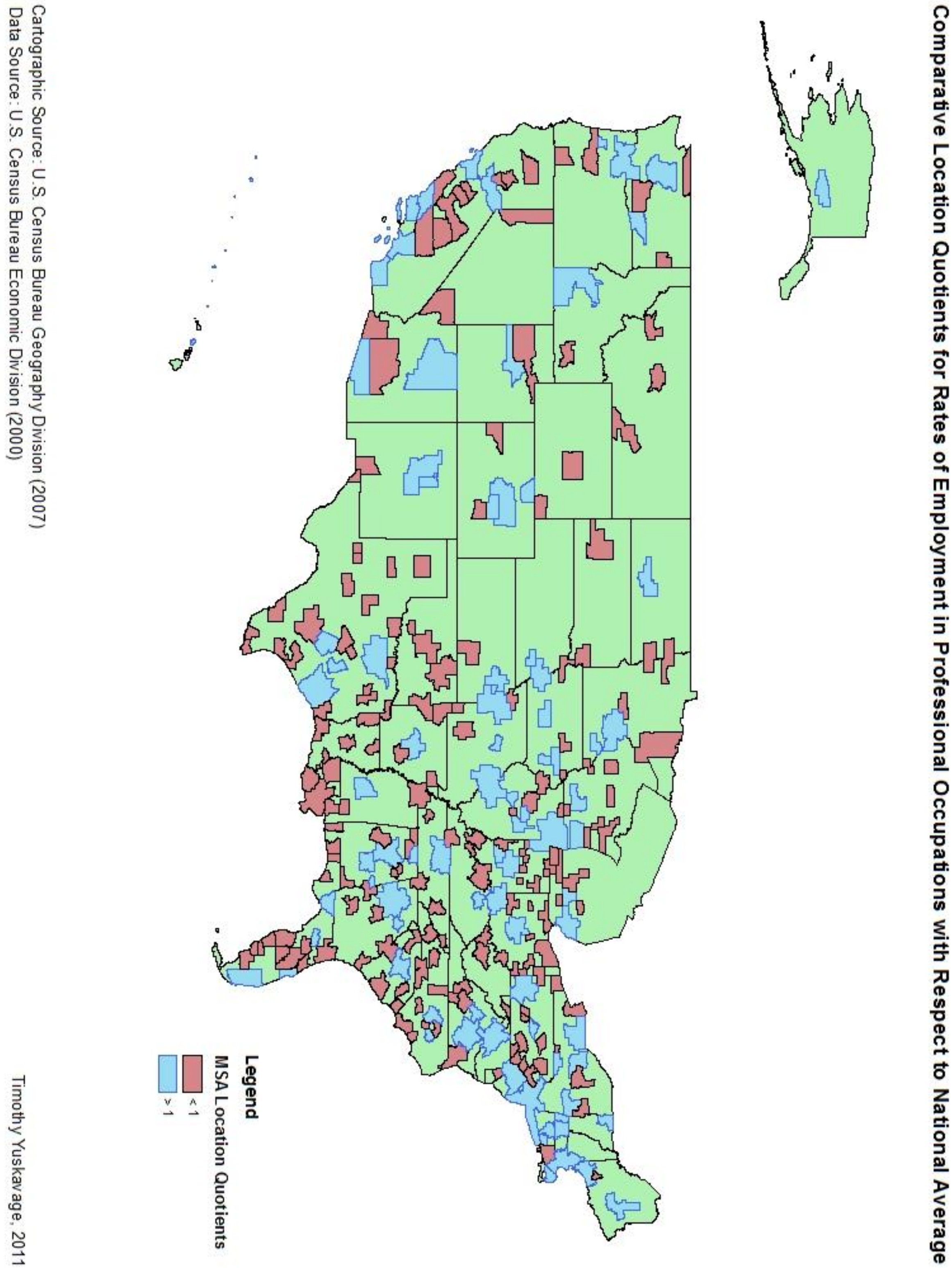
Comparative Location Quotients for Rates of Employment in Professional Occupations with Respect to National Average
Legend
MSA Location Quotients
< 1
> 1
Cartographic Source: U.S. Census Bureau Geography Division (2007)
Data Source: U.S. Census Bureau Economic Division (2000)
Timothy Yuskavage, 2011

Figure 4 – Regions as defined by the U.S. Census Bureau

Region Code	Geographic Region
1	New England
2	North Atlantic
3	East North Central
4	West North Central
5	South Atlantic
6	East South Central
7	West South Central
8	Mountain
9	Pacific

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ACADEMIC VITA of Timothy P. Yuskavage

Timothy P. Yuskavage
7705 Elgar St.
Springfield, VA, 22151
tim.yuskavage@gmail.com

Education Bachelor of Science Degree in Geography, Human Geography Option. Penn State University, Spring 2011

Bachelor of Science Degree in Economics. Module in International, Development & Transition Economics. Penn State University, Spring 2011.

Honors in Geography
Thesis Title: Shares Of Employment In The Knowledge Sector Among Metropolitan Area Economies
Thesis Supervisors: Rod Erickson, Ed Coulson

Related Experience

Analyst intern with National Geospatial-Intelligence Agency. Performed intelligence analysis, research, and technical writing related to the mission of the agency. May-August 2009, June-August 2010.

Economist intern with Bureau of Economic Analysis. Helped introduce geographic informational systems into analysis and production in the Regional Product Division. May-August 2008.

Awards

Top Graduate, Geography Class of Spring 2011.
Dean’s List all semesters.
Phi Beta Kappa
Phi Kappa Phi
Gamma Theta Upsilon (Geography Honor Society)