ESSAYS ON THE SPATIAL ANALYSIS OF MANUFACTURING EMPLOYMENT IN THE U.S.

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by

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CHAPTER 1

INTRODUCTION

The manufacturing sector plays a role in the U.S. economy that is not only vital to the health and prosperity of the economy as a whole, but also one that is unique. At a House Subcommittee hearing on “Manufacturing R&D: How Can the Federal Government Help?” in 2003, Professor Thomas Eagar of M.I.T. testified that “to live well, a nation must produce well.” According to Professor Eagar, the only wealth-producing economic sectors are agriculture, mining, manufacturing, and construction; other sectors, such as services and trade, can only redistribute this wealth. Furthermore, unlike agriculture and mining, manufacturing is not directly limited by natural resources, and unlike construction, manufacturing products are easily exported. Consequently, Professor Eagar stated, “manufacturing is and will continue to be the fundamental base for the economic health and security of the United States” (Eagar 2003).

However, is the U.S. manufacturing sector collapsing? Professor Eagar disagrees. He cites data from the 1997 economic census which shows that the payroll of the U.S. manufacturing sector is 14% larger than the next two largest sectors (finance and insurance, and retail trade) combined, despite having 15% fewer employees. Peter Goodman of the Washington Post also says no. He reports that the U.S. remains by far the world’s leading manufacturing economy, producing more manufactured goods today than ever before, and three times as much as in the mid 1950s. He cites data from the Bureau of Economic Analysis estimating the value of American manufacturing at $4.5 trillion in 2005, up from $1.3 trillion in 1977. This represents almost one-fourth of world
manufacturing, about the size of Japan’s and Germany’s manufacturing sectors combined. Japan ranks second but its share is falling, while China’s share is growing but is still only 10 per cent of world manufacturing (Goodman 2007).

Daniel Ikenson, Associate Director of the Center for Trade Policy Studies at the Cato Institute, not only does not fear a manufacturing decline, but claims the U.S. manufacturing sector is thriving. “In 2006, the sector achieved record output, record sales, record profits, record profit rates and record return on investment. American manufacturing performance has never been stronger. Nor was 2006 an aberration. Since the nadir of the manufacturing recession in 2002, all of those indicators have been trending upward” (Ikenson 2007).

In his preview of the 2007 Economic Report of the President, Dr. Edward Lazear, Chairman of the Council of Economic Advisers, confirms that there has been a significant upward trend in the value of the manufacturing sector’s output for the past half century. Not only that, as shown in Figure 1-1, the growth in manufacturing output has been sizable enough to outpace the population growth (Lazear 2007).
On the other hand, while the value of the manufacturing sector may not be declining, employment in the manufacturing sector is. Data from the Bureau of Labor Statistics indicate that manufacturing’s share of total employment fell from more than 25 per cent in 1960 to less than 13 per cent in 2003 and continues to shrink. An Economic and Budget Issue Brief prepared by the Congressional Budget Office reports that between 2000 and 2004, the manufacturing sector lost more than 3 million jobs, a decrease of 17.5 per cent. As shown in Figure 1-2, the level of manufacturing employment is now at its lowest point since 1950 (Brauer 2004). In contrast, employment in the services sector increased by 17.9 per cent between 1990 and 1997, and by 13.2 per cent between 1997 and 2003. Dr. Lazear concedes that the U.S. economy, like all developed countries, is “heavily a service economy.” Service sector
employment accounted for about 56 per cent of total employment in 1960 and grew to about 73 per cent in 1994. Currently, 77 per cent of private production and 84 per cent of payroll jobs are in the services sector (Lazear 2007). While this is in a league with other developed countries, no other advanced economy has a higher services employment share.

![Diagram of Manufacturing Employment](image)

**Figure 1-2.** Manufacturing employment. Source: Brauer (2004).

What accounts for the decline in manufacturing employment? In the short run, fluctuations in manufacturing employment correlate to business cycles. This is evident from the vertical bars in Figure 1-2 above, which indicate periods of recession as defined by the National Bureau of Economic Research. The recession which started in 2001 was particularly challenging for the manufacturing sector, with job losses persisting through the first two years of the modest recovery. Brauer (2004) predicts, however, that long-run effects will keep the manufacturing sector from returning to its pre-
recession level even after the economy has fully recovered. Among these long-run influences are: (1) competition from foreign producers, (2) manufacturing productivity, (3) a shift in demand away from manufactured goods, and (4) changes in the structure of manufacturing employment.

Does the move out of manufacturing and into services reflect the pressures of foreign imports, in particular the recent trade with China? Brauer (2004) documents a surge in the bilateral trade deficit with China from $18.3 billion to $124 billion between 1992 and 2003. This swelled the trade deficit with China to a level beyond that with any other country. He also notes, however, that much of the increased imports from China point toward a shift away from other Pacific Rim countries. At the same time that U.S. imports from China increased from 5 per cent in 1992 to 12 per cent in 2003, combined imports from Australia, Brunei, Hong Kong, Indonesia, Japan, Korea, Macao, Malaysia, New Zealand, Papua New Guinea, the Philippines, Singapore, and Taiwan decreased from 34 per cent to 21 per cent.

Josh Bivens of the Economic Policy Institute, on the other hand, strongly opposes what he calls the exoneration of international trade flows for the “hemorrhaging job losses” in the U.S. manufacturing sector. He shows evidence that the rising trade deficit in manufactured goods accounts for 58 per cent of the decline in manufacturing employment between 1998 and 2003, and 34 per cent of the decline between 2000 and 2003 (Bivens 2004).

Bivens considers the rapid decline of U.S. manufacturing “a policy-induced crisis that warrants policy solutions” and calls for dollar relief and trade relief. First and foremost he blames the overvalued U.S. dollar. When a currency is overvalued, that country’s exports become more expensive to foreign buyers, while imports become less
expensive to domestic buyers. With U.S. products uncompetitive in the world market, the overall trade deficit (the difference between the volume of a nation’s exports and imports) rose by $411 billion between 1995 and 2004. Manufactured goods accounted for $408 billion of that increase. By the end of 2002, the manufacturing trade deficit stood at $491 billion, which means that $491 billion of domestic demand for manufactured goods is supplied by foreign producers and does not translate into increased domestic production and employment. Bivens estimates that balancing the trade account of the U.S. may translate into an employment gain as high as 3.6 million jobs (Bivens, 2003).

Bivens (2003) also points out that the huge job losses in manufacturing, caused by the overvalued dollar, have meant that many firms in that sector face large legacy costs for their retirees. Legacy costs are obligations by firms to pay contractually agreed-upon pension and health care benefits to retirees. Historically, the manufacturing sector has been more likely than any other sector to offer adequate retirement benefits, so that firms in this sector face a disproportionate share of the nation’s legacy costs. Since the competitive position of the U.S. manufacturing firms in global markets has been undermined, due to a rising trade deficit that is entirely beyond their control, these firms are no longer able to meet their obligations. In addition, massive job losses have caused many manufacturing workers to retire early, compounding the problem.

Lazear (2007), on the other hand, simply dismisses any link between a growing trade deficit and a declining manufacturing sector. In his view, the loss of manufacturing jobs as a share of the labor force began after the Second World War and has been steady. During that same time, the trade deficit rose, then fell, then rose again, with no
obvious parallel over time between a rising trade deficit and a declining manufacturing sector.

Ikenson (2007) takes the foreign trade argument one step further and claims that “not only is the U.S. manufacturing sector thriving, it is thriving in large measure because of international trade.” He supports his argument with the fact that in 2006, for example, 55 percent of all U.S. goods imports were industrial products and components. A positive correlation between a rising trade deficit, indicative of rising imports, and rising output in the manufacturing sector has been observed for decades, he writes. “While misguided (or disingenuous) politicians rail against the rising trade deficit, they fail to comprehend (or acknowledge) that U.S. producers are America’s largest importers... Imports and output rise in tandem. Thus, policymakers who seek to restrain imports are effectively advocating a manufacturing recession.”

While Professor Eagar does not address the issue of increasing trade deficits, both he and Dr. Lazear see a great deal of likeness between the evolution from manufacturing to services that has taken place since the second half of the twentieth century, and the industrial revolution that transformed the U.S. from an agricultural economy a century earlier. Figure 1-3 shows these structural changes in the U.S. economy. Here the contention is that the perception of a crisis in manufacturing is really the result of large gains in productivity over the past 50 years. Just as with the agricultural sector before, productivity gains have meant that the manufacturing sector can produce ever more goods, and can do so with less labor. Compared to 50 years ago, today’s manufacturing worker can produce more than four times as much. In 1950, $253 billion of output in manufacturing was produced by 14 million workers, the equivalent of about $18,000 per worker. Today, the 14.2 million workers in
manufacturing produce, on average, $107,000 each (Eagar 2003, Lazear 2007). Therefore, according to Lazear (2007), workers have been able to move to the services sector while output in manufacturing has continued to grow.

The U.S. has evolved from an Agriculture Economy to an Industrial Economy to a Service Economy

![Graph showing the evolution of the U.S. economy from Agriculture to Industry to Services]

Figure 1-3. Evolution of the U.S. economy. Source: Lazear (2007).

One of the most difficult realities of large gains in productivity, according to Eagar (2003), is the fact that the additional capacity almost always exceeds increased consumption. As the real output of the manufacturing sector has risen, the relative prices of manufactured goods have fallen. However, total spending on manufactured goods has also fallen, because the larger quantities purchased by households and firms are not enough to offset the lower prices (i.e., the price elasticity of demand is too low). Furthermore, Brauer (2004) and Lazear (2007) perceive a shift in demand away from
manufactured goods toward services, most notably health care, but also purchased services formerly performed within households. In contrast, Bivens (2004) sets aside both arguments. “Demand for manufactured goods would have to be extraordinarily unresponsive to price changes … to not compensate in a significant way for the rapid productivity increases in generating employment.” In addition, he rejects the notion of a long-term demand shift away from manufactured goods. Failure to incorporate imported manufactured goods when measuring demand for manufactured goods presents a misleading picture.

Finally, some of the decline in manufacturing employment in recent years may be due to changes in the structure of manufacturing employment. Bill Testa of the Federal Reserve Bank of Chicago wonders whether we are overestimating the loss of manufacturing employment as work formerly counted in the manufacturing sector is now attributed to service sectors. The ratio of production to non-production workers has decreased from 6 in the 1950s to 2.4 today (Testa and Mattoon, 2004). Brauer (2004) points out that manufacturers increasingly avoid adding permanent staff, instead meeting short-term fluctuations in demand by hiring temporary workers through agencies and contracting out support services. These workers are tallied as services rather than manufacturing.

Within this context and amidst this fray, the next three chapters of this dissertation represent three separate essays, each with a different perspective on the shift in employment trends from manufacturing to services. They have in common, though, that all three essays attempt to further establish the importance of manufacturing in the region under study and/or in the U.S. economy as a whole. A variety of statistical
The first essay (Chapter 2) addresses the clustering of economic activities across regions as an important source of innovation. In “The Competitive Advantage of Nations” (1990), Harvard business economist and strategy theorist Michael Porter described industry clusters as geographic concentrations of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities. Examples include such obvious clusters as computers in Silicon Valley or automobiles in Detroit. The benefits deriving from the interactions among firms in clusters through innovation are referred to as increasing returns. In Chapter 2, statistical tools to detect “hotspots” in space are used to explore the geographic landscape for the clustering of manufacturing and service sector jobs. These spatial statistical techniques model the interaction between firms in various industries that are located in close geographic proximity. In addition, they can model the economic interactions.

Trade linkages across clusters will vary in degree or strength; that is, an industry may be associated with one group of sectors more closely than with others. Therefore, once geographic clusters of economic activity have been identified, a cluster of eight counties in Northeast Ohio is examined in greater detail for the strength of its forward and backward linkages among economic sectors. A variety of economic-base and input-output analytical methodologies are used for this. Based on the relative strengths of these linkages, key-sector analysis will then be able to identify those industries that are of greatest importance to the economic health and prosperity of this cluster.
Almost without exception, authors involved in the research on manufacturing employment attempt to relate to their readers the human reality of massive job losses. The second essay (Chapter 3) addresses the ongoing debate concerning the merits or dangers of an evolution towards a “New Economy,” dominated by service sector jobs. In order to better inform this argument, Chapter 3 concentrates on an area of the U.S. that has “borne the brunt” of manufacturing job losses: the Great Lakes states (Wial and Friedhoff, 2006). Employment growth and job loss patterns are modeled over space and time, to provide a visual picture of where employment has been and where it is now. Visualization of these patterns is improved when the geographic distribution of the manufacturing sector employment growth is modeled and smoothed using a spatial statistical technique called kriging. In addition, kriging provides a powerful stochastic interpolation methodology to estimate missing values. The public use data drawn on for this dissertation contains a number of missing data points, where information is withheld as a result of confidentiality concerns. As opposed to other, deterministic interpolation methods, a stochastic methodology such as kriging allows for standard inference procedures to assess the validity of the interpolation results.

Finally, the third essay (Chapter 4) addresses the theoretical underpinnings for the widespread belief that the manufacturing sector serves as the engine that drives economic prosperity. In particular, the work of Nicholas Kaldor is reviewed, whose three “laws” first described the increasing returns or benefits that are endogenous in a strong manufacturing sector. In order to determine whether manufacturing is a better engine of economic growth than services, the empirical analysis incorporates the spatial autocorrelation and heterogeneity that has been found in Chapters 2 and 3 in a spatial autocorrelation model. Failure to take into account the spatial characteristics of the
variables violates the classical assumptions of statistical inference. More importantly, however, spatial models allow for the economic interpretation of the spatial interactions between variables.

1.1 Works Cited


CHAPTER 2

A SPATIO-TEMPORAL ANALYSIS OF THE U.S. MANUFACTURING AND SERVICE SECTORS

2.1 Introduction

There is a new paradigm in regional economic development: industrial clusters and cluster-based strategies to enhance global competitiveness and foster regional economic growth. This new paradigm has caught the attention of policymakers as well as academicians in regional and organizational science. Almost all state and many local governments are actively involved in the development of policies and strategies to capitalize on existing clusters, strengthen emerging clusters, or build new clusters from the ground up. Increasingly, these governments partner with local colleges and universities or with private consultants in their efforts. Websites abound where public or private institutions report on their cluster studies or offer guides to effective cluster development.

Much of the credit for engendering this wide-spread interest goes to Michael Porter’s book, *The Competitive Advantage of Nations* (1990) and his cluster-mapping project. Even though there is no consensus on the precise definition of an industry cluster by any means (in spite of the fact that everyone agrees on examples such as computers in Silicon Valley or automobiles in Detroit), almost every website, article, or research study on industry clusters either cites Porter or uses his definition. What makes this so remarkable is that in trying to answer the question of how and why firms
cluster, the spotlight is not on the firm, but on inter-organizational networks, geographic proximity, and innovation through knowledge transfers. This is an intriguing departure from the usual focus of policymakers and researchers, which has traditionally been on firm-specific resources (Oerlemans and Meeus, 2005).

The recurrence of interest in the geography of economic activity is even more noteworthy given the modern perception that “geography is dead;” i.e., that distance, place, and geography have lost their place in the economic landscape. Florida (2003) illustrates this notion by quoting from Kelly’s (1998) *New rules for the New Economy*: “the New Economy operates in a ‘space’ rather than a place, and over time more and more economic transactions will migrate to this new space . . . People will inhabit places, but the economy inhabits space.” Kelly defines space as an electronically created environment, with unlimited dimensions, not bound by proximity. He sees a market space rather than a market place, with communication at its core: “Communication is not just a sector of the economy. Communication is the economy.” Since sophisticated telecommunications systems, the internet, and low-cost transportation systems are thought to eliminate the need for people to live where they work, it is assumed that they won’t. Firms will benefit from increasing returns by belonging to a network in space, not in a place.

Florida (2003) goes on to say, however, that In spite of Kelly’s prediction, it appears that “place, rather than being an abstract ‘space’ as Kelly suggests, is essential to economic life.” Most of the literature on industrial clusters suggests that as firms locate in physical proximity to one another, spillovers of knowledge, people, and technology will occur that in turn lead to productivity increases and cost benefits for all
firms in the cluster (Scorsone, 2002, Vom Hofe and Chen, 2006). This would indicate that where economic activity takes place matters, or that “geography is alive and well”.

Geography plays a more or less important role in the way researchers define industrial clusters. For example, Doeringer and Terkla’s (1995) definition as “geographical concentrations of industries that gain performance advantages through co-location” comes close to describing agglomeration economies; that is, the existence of externalities that result from spatial concentration such that spatial concentration creates a favorable environment for business, productivity, and economic growth. In their words, “the presence of positive externalities explains the clustering process, whereas specific location sites for each cluster depend on either ‘historical accident’ or the cost advantages provided by immobile factors that attracted the firms anchoring the cluster.” Business externalities, agglomeration economies, labor pooling, and knowledge spillovers are some of the cluster drivers they identify.

Porter (1990), too, assigns a key role to geographic proximity. His Diamond of Advantage, now incorporated in most college-level textbooks in business and economics, identifies four major factors to which any given firm can trace its success: (1) the nature of firm strategy, structure and rivalry in the country; (2) factor conditions; (3) demand conditions; and (4) the presence of related and supporting industries. While his original thesis concerned the competitive advantage of nations, he soon recognized that the majority of economic activity takes place at the regional level. This is reflected in his definition of industry clusters as “geographic concentrations of interconnected companies, specialized suppliers, service providers, firms in related industries, and associated institutions (e.g., universities, standard agencies, and trade associations), in particular fields that compete but also cooperate” (Porter, 1998). He distinguishes
vertical from horizontal clusters, with different economies. Vertical clusters are made up of industries that are linked together through buyer-seller relationships; horizontal clusters include industries that may share a common market for the end products, use a common technology or labor force skills, or require similar natural resources.

According to Bergman and Feser (1999), on the other hand, geographic concentration does not fit the basic definition of an industry cluster. Instead, they stress the relationship between business and non-business organizations for whom membership within the group is an important element of each member firm’s individual competitiveness. Binding the cluster together are “buyer-supplier relationships, or common technologies, common buyers or distribution channels, or common labor pools” (Enright, 1996). The implication in this definition is that a cluster may be more or less geographically concentrated, and that interdependence between enterprises may be distance-sensitive to varying degrees.

Two strands run through the literature that is concerned with the identification of industry clusters. Most studies use qualitative methods (such as case studies) to first document the presence and nature of inter-firm ties in well-known clusters. They then complement their analysis with quantitative methods (Doeringer and Terkla, 1995; Jacobs and DeMan, 1996; Rosenfeld, 1997). Some studies, on the other hand, identify clusters strictly on the basis of quantitative analysis, including location quotients and input-output (I-O) analysis (Rosenfeld, 1997; Bergman, Feser, and Sweeney, 1996; Sohn, 2004). I-O analysis is useful for the quantitative evaluation of vertical integration, although it does not address whether there really is what they call a “value-chain” relationship between the individual firms, nor does it account for other inter-firm ties.

However, the measures of industry concentration or regional specialization used in most
quantitative studies (e.g., location quotient, Gini coefficient) are global measures that only detect overall inter-industry location patterns within the study region. These measures may indicate that a region specializes in a particular industry, but provide no information as to where. To change that, Feser, Sweeney, and Renski (2005) use a local indicator of spatial association (LISA) to pinpoint the actual locations of various clusters first identified by I-O analysis. Thus, they are able to map discrete clusters of various value-chain activities. They see their efforts as largely exploratory, producing descriptive information about the changing geography of U.S. production to be used for formal tests of location theory.

Within this context, the present paper draws on previous research by Helsel, Kim, and Lee (2006) to compare the geographic patterns of U.S. manufacturing and services activities across U.S. counties, and to trace their evolution over time. Like Feser, Sweeney, and Renski (2005), it is an exploratory study. Specifically, I use spatial analysis to identify geographic concentrations or “hotspots” of counties with comparatively high levels of manufacturing and/or service sector employment levels, and examine changes in these clusters of economic activity over the 1990-2003 period. I then zoom in on one of those clusters to examine its economic structure in greater detail. In particular, I will focus on industry interconnectedness within the cluster. Tighter linkages between firms have been found to provide agglomeration externalities that are linked to competitive advantage (Midmore, Munday, and Roberts, 2006). I will use input-output analysis to estimate the strength of backward and forward linkages between industries and identify key industries for the local economy.

The remainder of this paper proceeds as follows. Section 2 provides a historical and theoretical background that informs modern industrial cluster theory, as well as a
review of the current literature on industry clusters and their development. Section 3 discusses the methodology, including the identification of data sources and a discussion of the statistical measures used. The results of the analysis are reported in Section 4, which also provides information on future research directions that will emanate from this study.

2.2 Historical and Theoretical Background

As early as 1900 and 1905, the Census of Manufactures documented that U.S. industrial activities have a tendency to concentrate in certain geographic areas (Shelburne and Bednarzik, 1993). This spatial embeddedness was recognized by Alfred Marshall (1920), who coined the term “economies of localized industries” to describe the benefits accruing to firms located within an “industrial district”, a geographically concentrated cluster specializing in the production of a narrowly related set of goods. According to Marshall, increasing returns (the avoidance or forestalling of diminishing returns to capital) can arise not only internally, but also from external sources. Firms that are clustered together have the benefit of access to specialized suppliers, skilled labor, and an environment conducive to the spillover of technological knowledge from one firm to the other. Thus, external economies accrue from the cost savings of resource-sharing and information exchange that occur within a localized industrial environment (Cohen and Fields, 1998).¹

¹ The terms economies of scale, scale economies, and increasing returns (to scale) are often used interchangeably. Internal increasing returns, stemming from the internal operations of a firm, lower per-unit cost by extending the downward slope of its average long-run cost curve over a greater quantity of output. External increasing returns result in a downward shift of the average long-run cost curve.
Krugman (1991) revisits the notion of increasing returns. In his “New Economic Geography” model, opposing forces of agglomeration (also called centripetal forces), pulling economic activity towards existing locations, and of dispersal (also called centrifugal forces) interact to determine city size and location. Centripetal forces include market-size external economies (backward and forward linkages, thick labor markets), natural site advantages, and pure external economies (knowledge spillovers). Centrifugal forces include dispersed natural resources, market-mediated forces (transportation costs, urban land rent), and non-market forces (congestion, pollution). These opposing forces result in a spatially uneven economic landscape, dotted with highly concentrated clusters of economic activity.

The regional science literature abounds with well-known industrial clusters, including computers and software in Silicon Valley, biotechnology in Boston’s Route 128, aerospace and software in Seattle, and automobiles in Detroit (Feser, Sweeney, and Renski, 2005). The relationship among firms in a cluster can be classified as either vertical or horizontal. A vertical association among firms exists when they engage in typical direct buyer-seller transactions, such as in supply chains. Many supply chains develop around large anchor firms. A horizontal association among firms exists when they are connected by a common set of customers, have common infrastructure needs, or share a demand for similar technologies, distribution channels, skilled workers and other resources (Carnegie Mellon, 2002).

Clusters develop because they increase firms’ ability to compete in an increasingly global market. Firms recognize that they can achieve more together than they could individually. Clusters allow businesses access to more suppliers and customized support services, to better skilled and experienced labor pools, and to
greater opportunities for transfer of information and knowledge. The advantages of spatial concentration of industrial activities due to scale economies are often referred to as agglomeration economies. Sohn (2004) classifies these advantages as intra-industrial and inter-industrial. Intra-industrial concentration means that firms reap the benefits of a well-established infrastructure by locating in an area where there are already a large number of establishments in the same industrial sector. Inter-industrial concentration derives its benefits from backward/forward linkages. Agglomeration economies may enhance a region’s industrial development and potential for economic growth.

While many industrial clusters are self-organized, most state and local governments are actively engaged in the development of policies and strategies to capitalize on existing strengths, strengthen emerging clusters, or even build new clusters from the ground up. Increasingly, these governments partner with local colleges and universities in their development efforts. In some instances, universities independently engage in initiatives to promote cluster development in their area. Often, one of the challenges facing the successful implementation of such cluster development efforts is the ability to simply identify the locations of industry clusters. When clusters are seen as predominantly linked horizontally, research has focused on input-output analysis or related techniques to reveal what Feser, Sweeney, and Renski (2005) refer to as “value chain” linkages between firms or sectors, a term borrowed from the strategy literature. Qualitative research, particularly case study research, has been used to identify the codified or tacit transfer of knowledge and information among firms that would indicate the existence of industrial clusters. Only recently has there been more emphasis on
research attempting to account for sub-regional localization patterns and spatial cluster analysis (Feser, Sweeney and Renski, 2005).

Certainly, the crucial linkages between companies in an industrial cluster are not necessarily all location-dependent. In an increasingly global economy, many firms find that their membership in global production networks is as important to their competitiveness as their membership in any local ones. However, co-location has been identified as an important source of the externalities and spillover effects that drive industrial clusters. Therefore, this study attempts to identify geographic concentrations of manufacturing and service sector activities and analyze their evolution over time as a first step towards recognition and measurement of such externalities and spillover effects.

In addition, this study examines the economic structure of an existing cluster in Northeast Ohio, consisting of 8 counties: Portage, Summit, Cuyahoga, Geauga, Medina, Lake, Lorain, and Wayne. This cluster was identified as a hotspot of both manufacturing and service activities. Input-output analysis is used to estimate the strength of backward and forward linkages between the industries in this cluster, and identify key sectors as those whose backward and forward linkages within the cluster are stronger than average.

2.3 Methodology

2.3.1 Data and Units of Analysis

For this study, annualized employment counts were obtained from the U.S. Bureau of Labor Statistics (BLS) through its comprehensive Quarterly Census of Employment and Wages (QCEW), formerly known as the Covered Employment and
Wages (CEW) program or ES-202. The QCEW program comprises those positions that are covered by state unemployment insurance laws. It measures employment by place of work, as opposed to place of residence, and may include multiple job holdings where they exist.

Counties are used as the primary spatial unit of analysis. The employment data cover county employment for the manufacturing and service sectors in the 48 continental states and the District of Columbia for the years 1990, 1997, and 2003. The North American Industry Classification System (NAICS) codes are used at the 2-digit level to classify and aggregate the employment data as either manufacturing (NAICS codes 31-33) or services (51: Information; 52-53: Financial activities; 54-56: Professional and business services; 61-62: Education and health services; 72: Accommodation and food services; 81: Other services).\(^2\) County employment data at the 3-digit NAICS level are used for the 8 counties that comprise the Northeast Ohio cluster identified in this study.\(^3\)

Benchmark I-O data tables for U.S. industries for 1997 available from the Bureau of Economic Analysis are used to identify forward and backward linkages and key industries.

### 2.3.2 Measure of Spatial Concentration

There are a number of ESDA techniques that can be used to assess spatial association or spatial autocorrelation in a geo-referenced dataset. Global measures of

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\(^2\) Prior to 2001, the ES-202 program used the Standard Industrial Classification (SIC) system. The data from 1990 and 1997 were reconstructed to conform to the 2002 version of the NAICS.

\(^3\) The Bureau of Labor Statistics withholds publication of UI-covered employment data for any industry level when necessary to protect the identity of cooperating employers. As the level of disaggregation increases, so does the incidence of missing data. This makes data analysis at a finer resolution impractical. Even at the 3-digit NAICS county level, some data had to be estimated by interpolation.
autocorrelation (e.g., Moran’s I, Geary’s C Ratio, or the general G statistic) calculate one statistic for the entire study area. However, since spatial processes are likely to be heterogeneous within the distribution itself, local indicators of spatial association (LISA) measures, which can detect spatial autocorrelation at a local scale, have gained increasing acceptance (Anselin, 1995; Unwin, 1996; Lee and Wong, 2001).

This study uses the Getis-Ord $G_i^*$ statistic, a LISA measure that is particularly suited to the detection of “hotspots” or spatial clusters around an individual location (Ratcliffe & McCullagh, 1999). The $G_i^*$ statistic is a multiplicative measurement of geographic concentration, developed by Getis and Ord (Getis & Ord; 1992, Ord & Getis; 1995; Getis and Ord, 1996). It can distinguish between spatial clustering of high values as opposed to low values of the variable under study, and is easily mapped for visualization and analysis.

The value of $G_i^*$ for each county is based on sector employment of the county itself as well as that of neighboring counties. Thus, whereas measures such as the simple location quotient, the locational Gini coefficient (Krugman, 1991), or Ellison and Glaeser’s (1997) index of localization would detect concentrations of employment growth within counties, $G_i^*$ provides a methodology that allows us to acknowledge spatial concentration that crosses county boundaries (Feser, Sweeney, and Renski, 2005). “Hotspots” in the geographic distribution of employment data are identified by finding the locations of clusters with high county employment levels compared to the U.S. average county-level employment for the sector in question.

To calculate the $G_i^*$ statistic, I start by constructing a symmetrical binary matrix (consisting of zero’s and ones) of spatial weights ($w_{ij}$). Such a matrix specifies neighboring counties $j$ to any given county $i$, based on the assumption that closely
neighboring counties have more interaction of industrial activities than counties farther away from one another. While spatial weights matrices, by convention, assign no weight to the ego, the $G_i^*$ statistic requires that $i$ is considered its own neighbor.

Helsel, Kim, and Lee (2006) use the “queen’s” convention as a method to ascertain neighbor relationships. The queen’s case is an adjacency-based specification that considers all surrounding counties of $i$ as neighbors so long as they share at least part of their boundaries (Lee and Wong, 2001). However, since U.S. counties vary greatly in size, with some counties in the western regions of the U.S. several times larger in geographic area than counties in the east, the queen’s convention may bias the results, particularly when second-order (small-size) effects are desired. Therefore, the current study builds on the previous research and also uses a fixed-distance weighting scheme for some of the analysis.

The distance measure used is based on the journey-to-work distance and time data from the 2001-2002 National Household Travel Survey (U.S. Bureau of Transportation) and the 2004 census (U.S. Census Bureau). These data indicate an average commuting time of 25.5 minutes on local highways, which translates into approximately 30 miles. Neighbors are thus defined as those counties which are within this distance of any given county, based on nearest distance.

The spatial weights matrices are then transformed into their row-standardized forms, with each weight divided by its row sum (Anselin, 1995):

$$w_{ij}^s = w_{ij} / \sum_j w_{ij}$$

so that each adjacent county’s weight is a percentage of the total interactions between neighboring counties within a given distance.
For each county, the $G_i^*$ statistic for a given data point can then be calculated by comparing the local mean employment (county $i$'s and all of its neighbors) to the global mean (for all counties in the continental U.S.), and is expressed in standard deviations from the mean, as follows:

\[ G_i^* = \frac{\sum_j w_{ij} x_j - W_i \bar{x}}{s \sqrt{n S_{ii} - W_i^2 / n - 1}}, \text{for all } j \]

where

- $x$ represents county employment;
- $w_{ij}$ is the spatial weight that defines neighboring counties $j$ to county $i$.
- $W_i$ is the sum of weights $w_{ij}$.
- $\bar{x}$ represents the mean of county-level sector employment growth for the U.S. as a whole [i.e., $\bar{x} = (\sum_j x_j) / (n - 1)$];
- $S_{ii} = \sum_j w_{ij}^2$, and $s^2 = (\sum_j x_j^2 / n - 1) - (\bar{x})^2$.

In essence, (and assuming $G_i^*$ is distributed close to normally), the results can be roughly interpreted as z-scores along a normal curve. Z-scores above 1.96 are statistically significant at the 0.05 alpha level, so that a county with a $G_i^*$ statistic in the manufacturing sector greater than 1.96 evidently has a higher employment growth rate in that sector than one would expect if the overall pattern were a random one. Such a county is considered part of a “hotspot”. Counties with $G_i^*$ values between 1 and 1.96 are interpreted as being part of “potential hotspots”.

The $G_i^*$ statistic is a relative measure. Consequently, when $x$ is set to equal sector employment levels in its realization, spatial first-order effects will tend to dominate the outcome. First-order effects are the variations in the mean value of the spatial
process, referring to a global or large-scale trend. Since population tends to concentrate into a small number of large metropolitan areas (urbanization), counties that contain larger cities, or those that have higher population counts because of their large geographical area, may be included as hotspots in almost every cluster by virtue of their size. Similarly, small counties with significant employment may be overlooked.

As noted by Feser, Sweeney, and Renski (2005), changes in first-order effects are not uninteresting in and of themselves (e.g., the rise of the Sunbelt and decline of the industrial Midwest). However, they will mask the second-order effects that are also of considerable interest; that is, the interactions between firms in close physical proximity in counties with sparser populations.

This study, unlike previous research, will contrast first and second order effects. To isolate second-order effects and account for the correlation in the deviations of employment levels from the mean on a smaller scale, the employment data have been normalized by county population. This allows for the examination of clusters of economic activity beyond the levels expected by their population.

2.3.3 Regional Input-Output Analysis

Trade linkages across clusters will vary in degree or strength; that is, an industry may be associated with one group of sectors more closely than with others. Therefore, once geographic clusters of economic activity have been identified, one such cluster will be examined in greater detail for the strength of its industrial linkages. A cluster of eight counties in Northeast Ohio, identified as a hotspot of both manufacturing and services employment, is chosen for this purpose. To identify the trade linkages between
industries within this cluster, I will use a variety of economic base and I-O analytical techniques.

According to Klosterman (1990), “The economic base technique is based on a simple causal model that assumes that the basic sector is the prime cause of local economic growth, that it is the economic base of the local economy.” The premise of this model is that some economic activities (often identified to be manufacturing, local resource-oriented industries, or government agencies) act as the “base” that is necessary for other industries within the region to exist. Basic industries are autonomous in that their economic well-being depends almost entirely on external factors. In contrast, non-basic or local-market-serving industries are mostly dependent on local business conditions. Basic economic activities are often (but not always) export-oriented; i.e., firms sell much of their output beyond the local market.

A region with a strong basic presence has more resilience against adverse local business conditions than one that is dominated by non-basic industries. Furthermore, the impact of basic industries on the local economy is disproportionate; in addition to their direct effects (share of output, income, employment, etc.), basic industries exert multiplicative indirect and induced effects as a result of their interconnectedness within the region. These interconnections are referred to as linkages, which may be backward (the purchase of local inputs), forward (the local downstream processing of output), or related to final demand (labor income spent locally). The economic base model posits that the prime determinant of a healthy and growing regional economy is the economic base.

The appeal of the economic base model lies in its fairly straightforward application and its resemblance to the Keynesian multiplier concept in macroeconomic
theory. In its simplest form, which assumes that there is no autonomous non-basic employment, total employment in a region is made up of basic and non-basic employment, with non-basic employment proportional to total employment. This allows for the derivation of a multiplier as follows (McCann, 2001):

\begin{align*}
T &= B + N \\
N &= sT \\
T &= \frac{1}{1 - s} B
\end{align*}

where

equation (5) follows from (3) and (4);

$T$ = total employment in the region;

$B$ = basic employment in the region;

$N$ = non-basic employment in the region;

$s$ = share of non-basic employment in total employment; and

$1/(1 - s)$ = economic basic multiplier.

It is generally assumed that manufacturing, mining, agriculture, and federal and state governments are basic sector activities because they rely largely on non-local conditions. In contrast, all other industries are assumed to be non-basic, or entirely dependent upon local conditions. More commonly, the Location Quotient (LQ) technique is used to systematically assign industries to either basic or non-basic sectors. LQs compare the proportion of employment in a particular industry within the local economy to the proportion of employment in that same industry within a larger reference economy (most commonly the national economy) and are estimated as follows (Miller, 1998; McCann, 2001):
where

\[ LQ_i^L = \frac{\frac{w_i^L}{\sum_k w_k^L}}{\frac{w_i^{Nat}}{\sum_k w_k^{Nat}}} \] (6)

\[ w_i^L \] is the employment level on the local level for industry \( i \), and

\[ w_i^{Nat} \] is the employment level on the national level for industry \( i \).

Interpretation of the LQ values is as follows:

1. \( LQ_i^L = 1 \): All employment is non-basic. The share of employment in this industry is the same in the cluster as it is in the U.S. as a whole. In economic base theory terms, this indicates that local production can just satisfy local demand, and none of these goods or services are exported to non-local areas.

2. \( LQ_i^L < 1 \): All employment is non-basic. The share of employment in this industry is less in the cluster than it is in the U.S. as a whole. Output from this industry is insufficient to meet local demand, thus requiring imports from non-local areas.

3. \( LQ_i^L > 1 \): Some employment is basic. The cluster has a greater share of employment concentrated in this industry than does the U.S. as a whole. It is assumed to be able to meet local demand and export the excess production. The share of employment that is greater than the U.S. is considered basic employment.

Location quotients assume that patterns of demand and labor productivity do not vary geographically; that there is no “cross-hauling”, that is, that regions do not simultaneously import and export a product or service; and that there are no exports
from the reference region (BenDavid-Val, 1991). Furthermore, data resolution matters; when data is aggregated into coarser NAICS levels, or different geographies, which industries are basic and which are non-basic can change. LQs are commonly used in practice in spite of these limitations, mainly because of their expediency. The ideal alternative would be to conduct surveys and obtain actual company specific data to measure the flow of resources into and out of a region. However, survey methods are costly to administer, require the willingness of firms to cooperate, and may have large sampling errors (BenDavid-Val, 1991; Schaffer, 1999).

Originally, regional science practitioners routinely used LQs for predictive purposes, to derive impact multipliers in order to analyze the potential effects of exogenous shocks to the local economy. It is in this use that their limitations are most critical. However, as is done in this paper, LQs are now used mostly as an effective tool to provide a broad overview of a local economy. In addition, as described below, they are used as a means of regionalizing national I-O relationships.

I-O analysis sees an economy as an interconnected system of industries that directly and indirectly affect one another. It is based on a detailed accounting of how industries interact with each other, with industries outside the region, and with final demand sectors. The structure of a typical I-O table is represented in Figure 2-1. Input flows, measured in dollars, are recorded in the columns, output flows in the rows. The nucleus of the I-O table in terms of characterizing an economy’s economic structure is the inter-industry transactions matrix, which makes up intermediate demand. Each column records the purchases, or inputs, of the industry in question from the industries in the rows. For each sector $i$ the value of total production $z_i$ is the sum of the intermediate demand $x_{ij}$ and final demand $y_i$:
\[ x_i = \sum_j z_{ij} + y_i \] ; or, in matrix notation: \[ \mathbf{x} = \mathbf{Z} \mathbf{x} + \mathbf{y} \] (7)

From the transactions matrix \( \mathbf{Z} \), a direct requirements table or technology matrix \( \mathbf{A} \) of production coefficients \( a_{ij} \) (also referred to as technical or input coefficients) can be calculated. Letting \( x_j \) represent total output, or supply, of industry \( j \):

\[ a_{ij} = \frac{z_{ij}}{x_j} \] or \[ \mathbf{A} = \mathbf{Z}\mathbf{\hat{x}}^{-1} \] (8)

where the circumflex denotes a diagonalized vector. Each element \( a_{ij} \) of the technology matrix \( \mathbf{A} \) shows how much of each producing industry \( i \)'s goods and/or services are required to produce one dollar's worth of the consuming industry \( j \)'s output. Thus, each column represents that industry's input mix, which, since I-O analysis assumes stable

Figure 2-1. Structure of the Input-Output table. Source: Sporri et al. (2007, adapted from Miller, 1998).
linear production relationships, describes its production function (Schaffer, 1999, McCann, 2001).

Inter-industry linkages were assessed by Chenery and Watanabe (1958) using the direct requirements matrix, with backward linkages for each industry represented by the column sums, and forward linkages by the row sums. However, this approach does not account for indirect effects (changes in industry final demand). To do so, the entire production relationship, including final demand, must be considered.

Rearranging equation (8) yields

\[ Z = A\hat{x} \]  

which is substituted into equation (7):

\[ x = (A\hat{x}) \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} + y = Ax + y \]

Solving for \( x \) expresses production as a function of final demand:

\[ x = (I - A)^{-1} y \]

where the \( (I - A)^{-1} \) matrix is referred to as the multiplier, Leontief inverse, or total requirements matrix. Each cell in this matrix indicates that for every dollar’s worth of product that industry \( j \) exports, industry \( i \) increases its production by the multiplier in the cell. The column totals represent the output multipliers for that industry. Rasmussen (1956) developed measures of backward linkage from the column totals, and of forward linkages from the row totals, respectively. Industry \( j \)’s backward linkage indicator measures the extent to which a $1 change in the demand for its product causes production increases in all industries; similarly, industry \( i \)’s forward linkage indicator
measures the extent to which it is affected by a $1 change in the final demand of all industries.

Hirschman (1958) designates as "key sectors" in a local economy those industries that have greater than average forward and backward linkage indicators. He normalized the Rasmussen backward linkage ($BL_j$) and forward linkage ($FL_i$) indicators as follows:

\[
BL_j = \frac{1}{n} \sum_{i=1}^{n} b_{ij} = \frac{1}{n} B_j = \frac{1}{n} \frac{1}{V} = \frac{1}{n} V \tag{12}
\]

\[
FL_i = \frac{1}{n} \sum_{j=1}^{n} b_{ij} = \frac{1}{n} B_i = \frac{1}{n} \frac{1}{V} = \frac{1}{n} V \tag{13}
\]

where

$B_j$ and $B_i$ are the column and row multipliers, respectively, of the $n \times n$ total requirements matrix $B = (I - A)^{-1} = [b_{ij}]$; and

$V = \sum_{i=1}^{n} \sum_{j=1}^{n} b_{ij}$

Those industries or sectors for which the normalized values of both the backward linkage and forward linkage indicators are greater than unity are considered key sectors.

Unfortunately, data to construct a regional direct requirements matrix are not readily available publicly\textsuperscript{4}. As in the economic base model, tables based on surveys of a

\textsuperscript{4} Three major vendors of regional input-output models are the U.S. Bureau of Economic Analysis (RIMS II); Minnesota IMPLAN Group, Inc. (IMPLAN Pro); and the Center for Urban Policy Research at Rutgers, The State University of New Jersey (RECON).
representative sample of firms in each industry in the local economy are the “gold standard” of regional I-O analysis. Because of the expense, national tables are often used as a proxy for regional tables, based on the assumption that local industry technology does not vary widely from the national average. The national tables must then be regionalized by adjusting the national technical coefficients $a_{ij}^{Nat}$ for local conditions through the estimation of regional purchase coefficients (RPC), $r_{ij}$, such that:

$$a_{ij}^L = r_{ij} a_{ij}^{Nat}$$

(14)

RPCs capture the proportion of local demand of industry $j$ that is fulfilled by each of the producers $i$ within the region. If it is assumed that this proportion is constant across the supplying industries, than the RPC matrix can be replaced by a vector of coefficients $r_i$ estimated as follows:

$$r_i = \begin{cases} 
\text{LQ}_{ij}^L & \text{if } \text{LQ}_{ij}^L < 1 \\
1 & \text{if } \text{LQ}_{ij}^L \geq 1 
\end{cases}$$

(15)

where a value of unity or greater for the LQ implies that all inputs needed can be supplied locally using the same technical coefficients as on the national level. A value of less than unity implies that the LQ represents the proportion of inputs that can be purchased locally (Miller, 1998).

### 2.3.4 Data Analysis

The exploratory spatial data analysis is conducted using ArcGIS (ESRI) and SpaceStat (TerraSeer) software. $G_i^*$ statistics are first calculated on county-level employment data with a spatial weights matrix that uses the queen’s convention. This allows first-order or large-size effects to dominate the outcome. Subsequently, $G_i^*$
statistics are calculated on county-level employment data normalized by population. These calculations use a spatial weights matrix based on a fixed distance of 30 miles from the county’s geographic centroid.

Excel and MatLab are used for the calculations involved in the I-O analysis for eight counties in Northeast Ohio. A 40-industry direct requirements matrix is calculated from the national 1997 benchmark input-output table. This direct requirements matrix is then regionalized using LQs and inverted into the regional total requirements matrix. Key sector calculations derive from this matrix.

2.4 Results

2.4.1 Clusters: First-Order Effects

The results of the $G_i^*$-based “hotspot” analysis are summarized in Figure 2-2. Panels (a), (c), and (e) show a temporal evolution in the distribution of hotspots and potential hotspots for the manufacturing sector. $G_i^*$ statistics are plotted for 1990, 1997, and 2003, with the darkest shaded counties ($G_i^* > 1.96$) indicating hotspots and the lighter shaded counties ($1 < G_i^* < 1.96$) representing potential hotspots.

The largest cluster, in terms of geographic area, is located in the Los Angeles/San Diego and Phoenix/Tempe areas (Far West and Southwest regions). Since these are large urban areas, this outcome is not surprising. It is interesting to note, however, that these clusters show consistent expansion over time, with potential hotspots heating up into hotspots farther east and north into Arizona and California, respectively, between 1990 and 1997; and again further north into California from 1997 to 2003. Furthermore, a potential hotspot is evident in 2003 north of the existing hotspot in Arizona up to the Utah border and into Nevada. Also in the Far West region, there is
Figure 2-2. “Hotspot” analysis using $G_i^*$ on employment data in the manufacturing and service sectors.

A manufacturing cluster in the Silicon Valley/Bay Area that has remained stable over time. On the other hand, a potential hotspot in northwest Oregon and a hotspot in
northwest Washington show signs of increasing manufacturing employment relative to
the national average over time.

The Southwest region, other than the Phoenix/Tempe cluster already mentioned
and significant but stable clusters in the Houston and Dallas/Fort Worth areas, is rather
devoid of manufacturing clusters, as are the Rocky Mountain and Plains regions. A
potential hotspot heated up into a hotspot over time in the Minneapolis/St. Paul area as
well as in the Pittsburgh area. A manufacturing hotspot that shows signs of cooling
down is noticeable along the border of Illinois and Missouri.

Figure 2-3 shows a close-up view of manufacturing employment in the “Rust
Belt” in the Great Lakes region between 1990 and 2003. The hotspots here have
remained stable or shown moderate improvement. Especially in the Milwaukee and
Chicago metropolitan areas, there are noticeable signs of expansion. A potential
hotspot in the Minneapolis/St. Paul area heated up into a hotspot over the study period,
as did a potential hotspot in the Pittsburgh area. Please note the swelling cluster in
Northeast Ohio, which will be investigated in more detail below.

Figure 2-3. Rust Belt manufacturing clusters, 1990 and 2003.
Service sector clusters are shown in panels (b), (d), and (f) of Figure 2-2. As expected, the geographic pattern of the distribution of services hotspots and potential hotspots over time and space fairly mimics that of the manufacturing sector, although the services clusters tend to be larger. As with manufacturing, the largest services clusters in terms of geographic area are found in California and Arizona, with these clusters also showing substantial evolution from potential hotspots into hotspots over time. What is interesting to note, however, is that these services hotspots and their evolution appear to pre-date the evolution in manufacturing employment. Similarly, the evolution of an expanding services hotspot in the Denver area pre-dates a small potential manufacturing hotspot that first becomes evident there in 1997. In contrast, a potential manufacturing hotspot in northwest Utah in 1997 and 2003 coincides with the approximate geographic location of a service sector potential hotspot that does not appear until 2003. Furthermore, it should be noted that in the Pittsburgh area, where manufacturing is heating up, services appear to be cooling down.

2.4.2 Clusters: Second-Order Effects

Figure 2-4 shows the clustering of manufacturing and service sector employment across counties when the data is normalized by population. In addition, the weighting scheme used to calculate the $G^*$ statistics now is a fixed distance of 30 miles from the county geographic centroid, based on average commuting time and distance. It is not surprising, therefore, that the large-area counties in the western half of the U.S. are no longer included as hotspots. Compared to the first-order effects, the Great Lakes region shows some additional clustering, whereas the Southeast shows considerably more hotspots and proportional employment in 1990, diminishing over time. Considering that
Figure 2-4. Manufacturing and service sector employment normalized by population.
second-order effects magnify the variation in employment for counties with very small populations, increases in population in these small rural counties as a result of the industrialization may contribute to the decreased clustering over time.

The landscape for service employment normalized by population lacks the uneven spatial distribution that is so evident in manufacturing. It is dotted with many small potential hotspots and a few small hotspots throughout the U.S.; any larger clusters have diminished over time. This accentuates the differences in location patterns between manufacturing and services employment.

2.4.3 Northeast Ohio Cluster Profile

Among the identified clusters, the Northeast Ohio cluster was selected for closer examination. Figure 2-5 shows the study area. Cuyahoga County is the largest employer of both manufacturing and service sector jobs. Summit County is the second largest. In both counties there have been substantial reductions in manufacturing employment, offset by steady increases in services.
During the study period, Northeast Ohio has seen growth in a number of service industries, at the expense of manufacturing industries. As shown in Table 2-1, the greatest increases occurred in management services, followed first by accommodation and food services, and then by educational services. Information services declined throughout. Among the various manufacturing sectors, only textile mills show a modest increase in employment; however, even now their relative share in manufacturing employment is insignificant. Almost without exception, other manufacturing sectors exhibit a general trend of increasing decline. The greatest overall losses occurred in petroleum and coal products manufacturing, followed by apparel and beverage/tobacco products. However, the impact of the latter is much less than the former, since their share in local employment is much less.

Table 2-1. Manufacturing and service sector employment in the 8-county Northeast Ohio cluster.

<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>311</td>
<td>Food</td>
<td>11,363</td>
<td>10,086</td>
<td>10,079</td>
<td>-1%</td>
<td>-1%</td>
<td>-12%</td>
</tr>
<tr>
<td>312</td>
<td>Beverage/Tobacco Products</td>
<td>2,564</td>
<td>834</td>
<td>1,171</td>
<td>-67%</td>
<td>40%</td>
<td>-54%</td>
</tr>
<tr>
<td>313</td>
<td>Textile Mills</td>
<td>165</td>
<td>125</td>
<td>354</td>
<td>47%</td>
<td>181%</td>
<td>312%</td>
</tr>
<tr>
<td>315</td>
<td>Apparel</td>
<td>2,562</td>
<td>831</td>
<td>675</td>
<td>-68%</td>
<td>-19%</td>
<td>-74%</td>
</tr>
<tr>
<td>321</td>
<td>Wood Products</td>
<td>2,040</td>
<td>1,910</td>
<td>1,829</td>
<td>-6%</td>
<td>-4%</td>
<td>-10%</td>
</tr>
<tr>
<td>322</td>
<td>Paper</td>
<td>8,668</td>
<td>8,317</td>
<td>7,224</td>
<td>-4%</td>
<td>-12%</td>
<td>-16%</td>
</tr>
<tr>
<td>323</td>
<td>Printing/Related Support Activities</td>
<td>10,672</td>
<td>11,316</td>
<td>8,716</td>
<td>0%</td>
<td>-23%</td>
<td>-18%</td>
</tr>
<tr>
<td>324</td>
<td>Petroleum/Coal Products</td>
<td>5,679</td>
<td>954</td>
<td>593</td>
<td>-83%</td>
<td>-39%</td>
<td>-90%</td>
</tr>
<tr>
<td>325</td>
<td>Chemical</td>
<td>20,870</td>
<td>20,049</td>
<td>18,177</td>
<td>-4%</td>
<td>-3%</td>
<td>-13%</td>
</tr>
<tr>
<td>326</td>
<td>Plastic/Rubber Products</td>
<td>28,499</td>
<td>28,365</td>
<td>21,025</td>
<td>0%</td>
<td>-26%</td>
<td>-26%</td>
</tr>
<tr>
<td>327</td>
<td>Nonmetallic Mineral Products</td>
<td>5,054</td>
<td>5,039</td>
<td>5,619</td>
<td>0%</td>
<td>24%</td>
<td>24%</td>
</tr>
<tr>
<td>331</td>
<td>Primary Metal</td>
<td>27,522</td>
<td>22,381</td>
<td>14,217</td>
<td>-36%</td>
<td>-46%</td>
<td>-46%</td>
</tr>
<tr>
<td>332</td>
<td>Fabricated Metal Products</td>
<td>53,320</td>
<td>50,624</td>
<td>41,673</td>
<td>-5%</td>
<td>-18%</td>
<td>-22%</td>
</tr>
<tr>
<td>333</td>
<td>Machinery</td>
<td>34,110</td>
<td>33,922</td>
<td>23,915</td>
<td>-1%</td>
<td>-20%</td>
<td>-30%</td>
</tr>
<tr>
<td>334</td>
<td>Computer/Electronic Products</td>
<td>14,700</td>
<td>10,939</td>
<td>8,658</td>
<td>-20%</td>
<td>-19%</td>
<td>-40%</td>
</tr>
<tr>
<td>335</td>
<td>Electronic Equipment, Appliance, Components</td>
<td>13,837</td>
<td>12,604</td>
<td>9,083</td>
<td>-5%</td>
<td>-29%</td>
<td>-34%</td>
</tr>
<tr>
<td>336</td>
<td>Transportation Equipment</td>
<td>43,967</td>
<td>36,933</td>
<td>28,950</td>
<td>-15%</td>
<td>-23%</td>
<td>-35%</td>
</tr>
<tr>
<td>337</td>
<td>Furniture/Related Products</td>
<td>5,533</td>
<td>3,237</td>
<td>2,679</td>
<td>-41%</td>
<td>-11%</td>
<td>-49%</td>
</tr>
<tr>
<td>339</td>
<td>Miscellaneous</td>
<td>11,912</td>
<td>11,774</td>
<td>11,092</td>
<td>-1%</td>
<td>-6%</td>
<td>-7%</td>
</tr>
</tbody>
</table>

Note: Northeast Ohio cluster includes Portage, Summit, Cuyahoga, Geauga, Medina, Lake, Lorain, and Wayne counties.
Figure 2-6 shows the changes in location quotients for the manufacturing and service sectors, respectively. Location quotients represent the share of employment in the region relative to the share of employment nationally, and are used as an indicator of the region’s economic base. This figure indicates that the economic base for this cluster remains the manufacturing sector, in spite of employment losses. In the service sector, the increase in employment in management services that was noted above has turned this sector into a basic activity. In manufacturing, the most striking change is the loss of petroleum and coal products manufacturing as part of the region’s economic base. All of this job loss occurred in Cuyahoga County.

Table 2-2 shows the results of the key sector analysis for 2003. Key sectors are those that have both an above average power of dispersion for the backward linkages, and an above average sensitivity of dispersion for forward linkages (Sonis, Hewings, and Guo, 2000). In other words, the normalized indices for forward and backward linkages should both be greater than one in order for a sector be considered a key sector. Sectors with an above average backward linkage index are considered backward linkage oriented; similarly, sectors with an above average forward linkage index are considered forward linkage oriented. This classification is demonstrated in Figure 2-7.

Five key industries are identified, all in the manufacturing sector: primary metal, fabricated metal products, plastic and rubber products, chemical, and paper. Of these, primary metals fabrication has the strongest backward linkages, while the chemical industry has the strongest forward linkages. As can be seen from Table 2-2, key sectors do not necessarily have the strongest linkages. The transportation equipment sector has the strongest backward linkages, while the professional services sector is the most forward-linkage oriented.
Figure 2-6. Location quotients for the manufacturing and service sectors in the eight-county Northeast Ohio cluster.
Table 2-2. Indices of forward and backward linkages for the manufacturing and service sectors in the 8-county Northeast Ohio cluster.

<table>
<thead>
<tr>
<th>Sector</th>
<th>Linkage Indicator</th>
<th>Forward</th>
<th>Backward</th>
</tr>
</thead>
<tbody>
<tr>
<td>311  Food</td>
<td>b</td>
<td>0.8628</td>
<td>1.0100</td>
</tr>
<tr>
<td>312  Beverage/Tobacco Products</td>
<td>b</td>
<td>0.6122</td>
<td>1.0065</td>
</tr>
<tr>
<td>313  Textile Mills</td>
<td>b</td>
<td>0.6526</td>
<td>1.0965</td>
</tr>
<tr>
<td>314  Textile Product Mills</td>
<td></td>
<td>0.5971</td>
<td>0.9767</td>
</tr>
<tr>
<td>315  Apparel</td>
<td></td>
<td>0.5968</td>
<td>0.8573</td>
</tr>
<tr>
<td>321  Wood Products</td>
<td></td>
<td>0.6948</td>
<td>0.9672</td>
</tr>
<tr>
<td>322  Paper</td>
<td>Key</td>
<td>1.2595</td>
<td>1.2126</td>
</tr>
<tr>
<td>323  Printing/Related Support Activities</td>
<td>b</td>
<td>0.7641</td>
<td>1.1423</td>
</tr>
<tr>
<td>324  Petroleum/Coal Products</td>
<td></td>
<td>0.7272</td>
<td>0.9706</td>
</tr>
<tr>
<td>325  Chemical</td>
<td>Key</td>
<td>2.0145</td>
<td>1.2167</td>
</tr>
<tr>
<td>326  Plastic/Rubber Products</td>
<td>Key</td>
<td>1.0525</td>
<td>1.1994</td>
</tr>
<tr>
<td>327  Nonmetallic Mineral Products</td>
<td>b</td>
<td>0.7694</td>
<td>1.0031</td>
</tr>
<tr>
<td>331  Primary Metal</td>
<td>Key</td>
<td>1.5837</td>
<td>1.2913</td>
</tr>
<tr>
<td>332  Fabricated Metal Products</td>
<td>Key</td>
<td>1.2590</td>
<td>1.1469</td>
</tr>
<tr>
<td>333  Machinery</td>
<td>b</td>
<td>0.8370</td>
<td>1.2197</td>
</tr>
<tr>
<td>334  Computer/Electronic Products</td>
<td>b</td>
<td>0.9680</td>
<td>1.0707</td>
</tr>
<tr>
<td>335  Electronic Equipment/Apparces/Components</td>
<td>b</td>
<td>0.8096</td>
<td>1.2167</td>
</tr>
<tr>
<td>336  Transportation Equipment</td>
<td>b</td>
<td>0.9852</td>
<td>1.4141</td>
</tr>
<tr>
<td>337  Furniture/Related Products</td>
<td>b</td>
<td>0.5945</td>
<td>1.0146</td>
</tr>
<tr>
<td>399  Miscellaneous</td>
<td>b</td>
<td>0.6708</td>
<td>1.0760</td>
</tr>
<tr>
<td>51   Information</td>
<td>f</td>
<td>1.0864</td>
<td>0.9495</td>
</tr>
<tr>
<td>52   Finance/Insurance</td>
<td>f</td>
<td>1.5433</td>
<td>0.9473</td>
</tr>
<tr>
<td>53   Real Estate/Rental/Leasing</td>
<td>f</td>
<td>1.7246</td>
<td>0.7669</td>
</tr>
<tr>
<td>54   Professional/Scientific/Technical Services</td>
<td>f</td>
<td>2.0349</td>
<td>0.8254</td>
</tr>
<tr>
<td>55   Management of Companies/Enterprises</td>
<td>f</td>
<td>1.5421</td>
<td>0.8123</td>
</tr>
<tr>
<td>56   Administrative/Waste Management/Remediation Services</td>
<td>f</td>
<td>1.2106</td>
<td>0.8151</td>
</tr>
<tr>
<td>61   Educational Services</td>
<td></td>
<td>0.8039</td>
<td>0.9274</td>
</tr>
<tr>
<td>72   Accommodation/Food Services</td>
<td></td>
<td>0.7732</td>
<td>0.9094</td>
</tr>
<tr>
<td>81   Other Services</td>
<td></td>
<td>0.9929</td>
<td>0.9440</td>
</tr>
</tbody>
</table>

* Key linkage designation:
  - key = Key sector
  - b = backward linkage oriented sector
  - f = forward linkage oriented sector
4.4 Conclusion

This paper has contrasted the geographic distribution of manufacturing and service sector employment for U.S. counties, and has traced the evolution of their clustering patterns over the 1990-2003 study period. When no adjustment is made for geographic size or population, significant clustering is evident, and the patterns are similar for both manufacturing and services. An interesting observation is made: the clustering of the service sectors predates that of manufacturing. Since the $G_2^*$ depicts
clustering relative to the national average, it is not possible to fully explain this phenomenon from this measure alone. At first glance, it may seem that manufacturing is drawn to locations with well-established services; on the other hand, in light of the decline in manufacturing employment nationwide, another explanation may be that manufacturing is less likely to leave an area where services are ubiquitous. This will be a topic for future research, as well as the interaction between manufacturing and services.

When clustering is examined for employment data normalized by population, differences in location patterns between manufacturing and services become evident. Manufacturing employment relative to the population tends to cluster, service sector employment relative to the population is more dispersed. Furthermore, the clustering of manufacturing employment relative to the population diminishes over time. This is most likely due to the fact that populations tend to follow manufacturing employment. A strong manufacturing presence in a sparsely populated area tends to draw population to that area; while the same cannot be said for services. Again, this is an area that warrants further investigation.

An eight-county region in Northeast Ohio, where clustering of both manufacturing and service sector employment is evident, was further analyzed. Using regionalized input-output tables and key-sector analysis, it is apparent that in spite of a dwindling manufacturing presence, this area continues to be dependent on manufacturing, particularly primary metal, fabricated metal products, plastic and rubber products, chemical, and paper.
2.5 Works Cited


CHAPTER 3

KRIGING: A RESPONSE SURFACE ANALYSIS OF MANUFACTURING EMPLOYMENT IN THE GREAT-LAKES STATES

3.1 Introduction

Between 1997 and 2003, the manufacturing sector in the United States lost more than 3 million jobs, a decrease of 16.7 per cent, and the level of manufacturing employment is now at its lowest point since 1958 (Bivens, 2004). In contrast, employment in the services sector increased by 13.2 per cent during the same period, and by 17.9 per cent from 1990 to 1997. Globally, too, manufacturing has fallen to less than 20% of GDP in some OECD countries, and the role of services has become increasingly important, rising to over 70%. This begs the question: just as the last century saw the evolution from an economy dominated by agriculture and extractive industries to a highly industrialized one, are we now seeing an accelerated progression from the latter to a “New Economy”? Will service-producing industries obviate the need for a strong manufacturing base? “Not only does everybody believe this is happening, it really is happening,” reads one of the pages of a website maintained by entrepreneur John Walker, originator of AutoCAD.⁵ “For example, walk through any major city in the US and observe that there are four banks on every corner. If this were not a service economy, there would be, say, four machine shops.”

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⁵ The website reads further: “Except for a few clearly-marked exceptions, all the material on this site is in the public domain and may be used in any manner without permission, restriction, attribution, or compensation.” Since no exception was noted, there is no further citation.
Nowhere in the U.S. has the impact of manufacturing job losses been felt more than in the major cities of the Great Lakes states, particularly the metropolitan areas of Michigan, Ohio and Illinois. Wial and Friedhoff (2006) conducted a detailed study of job losses in the Great Lakes region for the 1995-2005 decade. They report that the majority of Great Lakes metropolitan areas saw reductions in manufacturing employment at a greater pace than the U.S. as a whole. In terms of manufacturing as a proportion of total employment, the greatest losses occurred in Canton, Ohio and Flint, Michigan. Chicago and Detroit lost the most jobs overall. In spite of these losses, however, the Great Lakes region continues to be manufacturing-dependent; that is, manufacturing’s share of total employment for many metropolitan areas in this region exceeds that of the U.S. (see Table 3-1).


<table>
<thead>
<tr>
<th>Metropolitan Area</th>
<th>Percentage of Total Jobs in Manufacturing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Evansville, IN</td>
<td>19.3%</td>
</tr>
<tr>
<td>Grand Rapids, MI</td>
<td>18.8%</td>
</tr>
<tr>
<td>Canton, OH</td>
<td>17.7%</td>
</tr>
<tr>
<td>Fort Wayne, IN</td>
<td>17.2%</td>
</tr>
<tr>
<td>Peoria, IL</td>
<td>16.7%</td>
</tr>
<tr>
<td>Youngstown, OH</td>
<td>16.7%</td>
</tr>
<tr>
<td>Milwaukee, WI</td>
<td>16.0%</td>
</tr>
<tr>
<td>Toledo, OH</td>
<td>15.5%</td>
</tr>
<tr>
<td>Akron, OH</td>
<td>14.6%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Metropolitan Area</th>
<th>Percentage of Total Jobs in Manufacturing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dayton, OH</td>
<td>14.3%</td>
</tr>
<tr>
<td>Cleveland, OH</td>
<td>14.0%</td>
</tr>
<tr>
<td>Flint, MI</td>
<td>14.0%</td>
</tr>
<tr>
<td>Detroit, MI</td>
<td>13.9%</td>
</tr>
<tr>
<td>Cincinnati, OH</td>
<td>11.9%</td>
</tr>
<tr>
<td>Indianapolis, IN</td>
<td>11.4%</td>
</tr>
<tr>
<td>Chicago, IL</td>
<td>11.1%</td>
</tr>
<tr>
<td>Ann Arbor, MI</td>
<td>10.7%</td>
</tr>
<tr>
<td>United States</td>
<td>10.7%</td>
</tr>
</tbody>
</table>
There is weariness surrounding the evolutionary pattern of the economic landscape. Is the manufacturing sector really on the way out? Are we losing our competitive advantage? If we don’t see a machine shop at every corner, is that an indicator of a lost manufacturing presence? Should we welcome the change into a service economy or forestall it? Before we can make predictions about an uncertain future, it is imperative to first have a thorough understanding of the past and the present. While studies such as Wial and Friedhoff (2006) provide a detailed analysis of the data, this article seeks to provide a way to visualize where we have been and where we are now in terms of the manufacturing sector that, to my knowledge, has not been used before. It is an exploratory analysis of the data that, it is hoped, will provide a basis for greater insight and further investigation.

This paper will depict the growth and subsequent decline in manufacturing employment in the Great Lakes region by employing a spatial-analytical technique known as kriging. This technique, which has its origin in geostatistics, is receiving increased attention. Its use is a departure from the usual choropleth maps, concentration maps, or box plots that are most often used to show variations in the distribution of data over space (Fitz-Simons, 2003). Kriging is a spatial interpolation method that smoothes the variation in the data across space, which enhances visualization of the geographic distribution of the variable under study. Figure 3-1 is an example of kriged pollution data (Fitz-Simons, 2003). A kriged surface map is easily combined with other features pertinent to the analysis, such as transportation networks, waterways, cities, etc., and is particularly beneficial when the intent is to show the evolution of a phenomenon over time. One can imagine fanning consecutive pages

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As Fitz-Simons (2003) points out correctly, some of the variation in the data is actually masked, which may or may not be a desirable result, depending on the purpose of the analysis.
containing kriged maps at various stages, to create an effect much like a movie. With
electronic media, such a movie is easily created.

![Figure 3-8. Example of a kriged surface. Source: Fitz-Simons (2003).](image)

In addition, the interpolation provided by kriging is different from other surface-
creating techniques in that it provides a stochastic surface, explicitly recognizing spatial
dependence and producing an estimation variance. In contrast, interpolation methods
such as Thiessen tessellation, inverse distance-weighting (IDW), or splines have been
variously referred to as “local deterministic methods” (Burroughs and McDonnell, 1998)
or “first-order interpolations” (Bailey and Gatrell, 1995), to distinguish them from the
second-order or predictive, statistics-based kriging method. This is particularly important
for research that uses publicly available employment data at finer, less aggregated
geographic levels such as counties, combined with industry-level detail. Such datasets
contain many missing values, suppressed because of confidentiality concerns. This
constitutes a serious limitation to their usefulness, unless an interpolation technique is applied that allows the researcher to gauge the reliability of the estimated values. Kriging does just that.

The following section discusses some aspects of the current debate between proponents of the New Economy and those who feel that the economic future of America can be safeguarded only by maintaining a strong manufacturing sector. Section 3 details the kriging methodology that will be used to illustrate the changing pattern of manufacturing employment in the Great Lakes region. The results of the analysis will be discussed in section 4.

3.2 Deindustrialization: The New Economy

The precipitous loss of manufacturing jobs in the U.S. has spawned a great deal of debate about its causes. Most often, blame is placed on globalization or the outsourcing of U.S. jobs to foreign countries, particularly China. However, the declining trend in manufacturing employment is not unique to the U.S.; all developed countries have seen a shift in jobs from manufacturing to services in varying degrees (OECD, 2000). This leads some researchers to conclude that while other factors may account for a small portion of the shift away from manufacturing, the true cause is a permanent and inevitable process of deindustrialization (Fisher, 2004).

There are those who find it natural and no cause for concern that the U.S. should enter into some form of post-industrial society, in which manufacturing industries are no longer singled out as having a major role to play as a source of rising living standards and prosperity. To Fisher (2004) there is no doubt that deindustrialization is an undeniable matter of fact, and an inevitable consequence of the process of
Schumpeterian creative destruction that is characteristic of capitalism. The very force that propelled manufacturing to become a primary source of prosperity in advanced economies – an “inexorable march of technological progress” – now has become the reason of its decline. With productivity gains obviating the need for manufacturing labor, innovations in high-tech sectors and other services have replaced manufacturing as the primary source of future prosperity. Just as trying to maintain inland water transportation, which until the end of the nineteenth century had been a major source of prosperity for Ohio for some time, would have been an impediment to the economic growth that resulted from the progression to a network of railroads, so, too, may attempts to maintain manufacturing employment hurt potential future increases in our standard of living.

Some go so far as to welcome a new era, and lament any obstacles that stand in the way of a “new economy.” For example, a report compiled under the auspices of the OECD Business and Industry Policy Forum starts: “Services are transforming OECD economies on a massive scale, but are still impeded by regulations and policies that stifle innovation and competition. Comprehensive reforms need to be pursued internationally as well as in individual OECD countries” (OECD, 2000). The OECD organized a Business and Industry Policy Forum, where senior government officials and business and trade union leaders discussed issues concerning “Realising the Potential of the Service Economy.” Their report finds it unfortunate that, consequent to a high degree of variation in underlying policy conditions, there is also considerable variation in the extent to which OECD countries have been able to experience rapid development of high-growth service industries.
In the U.S., firm reorganization around their core competencies has given rise to the outsourcing of a wide range of service activities, which is reflected in numerous start-ups of service companies. Furthermore, fueled by a growing body of Internet/ICT-related service providers, there has been a rapid increase in the development of highly sophisticated and innovative service products, particularly in the finance, insurance, and real estate sectors. Four interrelated reasons are given for these developments, which have altered the very structure of the U.S. economy: (1) lightly regulated product markets; (2) efficient markets for corporate control; (3) a strong supply of venture capital; and (4) a climate that is conducive to risk-taking and entrepreneurship (OECD, 2000).

The OECD report sees these developments in the U.S. as evidence of the value of a growing service sector to the economy, and as an incentive for other countries, where the conditions for change are less favorable, to implement policies that would remove any impediments to the process of deindustrialization. It should be noted, however, that within the framework of these developments the decline of the manufacturing sector and the rise of the service sector could also be interpreted as somewhat of a statistical artifact rather than a real structural change.

On the other hand, there are those who are loud in voicing their alarm and concern with regard to the process of deindustrialization. Among them is Fingleton (1999, 2000), author of “In Praise of Hard Industries: Why Manufacturing, Not the Information Economy, Is the Key to Future Prosperity.” Fingleton questions the wisdom of betting our future on post-industrialism. He laments: “The assumption is that manufacturing has now been decisively superseded by postindustrial services as the main engine of economic progress. … It is presented as revealed truth almost daily in the editorial pages of our great newspapers, and increasingly it is a fundamental driver
of American policy-making” (Fingleton, 2000). One of his concerns is that postindustrial services will create jobs disproportionately for a minority of the national workforce of above-average intellectual ability. Manufacturing, even the most advanced [knowledge-intensive] forms of manufacturing, offers a better balance of jobs for people at almost all levels of ability.

OECD (2000) disputes this. The report characterizes service industries as “a diverse group of economic activities that include high-technology, knowledge-intensive sub-sectors, as well as labour-intensive [sic], low-skill areas.” While the services and manufacturing sectors may be different in many aspects, these distinctions are blurring. For example, technological advances are changing the key attributes of services (i.e., intangibility, perishability, lack of transportability, lack of homogeneity, labor intensity, demand fluctuations, and buyer involvement). Furthermore, service providers are increasingly able to benefit from economies of scale. In a typical account of post-Fordism reaching services, the tale is told in terms of banks structuring financial assets such as mortgages into pools, and selling securities based on these pools to individual investors and portfolio managers. “Banks are focusing on producing a standardised [sic] product at a predictable rate, under standard norms of quality, and are teaching their workforces to produce that product as quickly and as efficiently as possible” (OECD, 2000).

Fingleton (2000) is particularly concerned with the differential effect on the U.S. balance of payments between manufacturing jobs and jobs in service industries, due to differences in the nature and location of these jobs. For example, 60% of sales for Microsoft – the “colossus of the New Economy” – went overseas in 1998. However, more than half of these sales generated value-added in Microsoft’s overseas
subsidiaries, not the U.S., so that the net positive effect on the balance of payments was only 20% of sales. Similarly, Merrill Lynch serves most of its overseas markets from local offices, not from the U.S., so that virtually all expenses in these markets are treated as deductions from its foreign revenues. As a result, less than 5 per cent of Merrill Lynch’s revenues are counted as exports. By comparison, traditional manufacturing giants such as Boeing derive close to 50% of their revenues from exports (Fingleton, 2000).

Wial and Friedhoff (2006) agree that manufacturing is critical to the American standard of living. They conclude: “The manufacturing-dependent metropolitan areas of the Great Lakes region, in particular, must retain and modernize their manufacturing bases if they are to remain economically viable. Advanced service industries, which in principle could have substituted for manufacturing as drivers of regional prosperity, have not generated enough jobs to offset recent manufacturing job losses.” They suggest a number of policy initiatives, both on the federal and local level. For example, they point to the artificial cost advantage now enjoyed by countries that lack enforceable labor and environmental standards, or that keep their currency artificially low. Domestically, the lack of some form of universal health care program places the burden of providing health insurance to workers and retirees on firms, a burden that may be too high for manufacturing firms struggling to stay profitable. This is where the federal government would have a role. At the local level, states “should expand their efforts to help manufacturers adopt cutting-edge technologies, reorganize work to increase productivity, and move into less price-competitive product markets.”

At a recent House Subcommittee hearing, M.I.T. professor Thomas Eagar refuted the notion that other sectors such as financial services or trade are able to
overtake manufacturing. According to the 1997 U.S. Economic Census, manufacturing has 15% fewer employees but a 14% larger payroll than the next two largest sectors combined (i.e., finance and insurance, and retail trade). There are only four economic sectors that generate wealth, Eagar said: agriculture, mining, manufacturing, and construction. Other sectors are built on the products created by the wealth generators, and only redistribute that wealth (Eagar 2003).

Eagar testified that the perception of a crisis is really the result of large gains in productivity over the past 50 years. He called it a manufacturing revolution that rivals the industrial revolution of the 19th century. The average U.S. productivity growth in manufacturing between 1950 and 2000 was 2.8% per year and has been accelerating over the past two decades (see Figure 3-2). Manufacturing productivity growth has exceeded the average of other sectors by more than 1% per year. Compared with 50 years ago, today’s manufacturing worker can produce four times as much. Competitive pressures, new technologies, and product and process innovations have contributed to this. As a result, Americans enjoy a much higher standard of living, with products becoming more useful and more affordable.

<table>
<thead>
<tr>
<th>U.S. Average Annual Productivity Gains</th>
</tr>
</thead>
<tbody>
<tr>
<td>All US Business</td>
</tr>
<tr>
<td>Manufacturing</td>
</tr>
</tbody>
</table>

Figure 3-9. Productivity gains. Source: Eagar (2003).
Even though consumption has increased, the reality is that neither it nor exports can keep pace with the increased capacity. Thus, firms decrease their workforce and often move their commodity production overseas, resulting in job losses. According to Eagar (2003), this is a natural process reflecting the lifecycle of industries. This is how the U.S. has lost textiles, shipbuilding, consumer electronics and much of the steel industry. Semiconductors are beginning to show signs of decline. Displaced workers must shift to new positions, which can be either beneficial or detrimental to them. The most important determinant of benefits resulting from such job shifts will be the presence of innovative new industries that bring high value to their markets. Manufacturing continues to be the key to prosperity; innovation, particularly the start-up of new industries, is the key to survival for the U.S. manufacturing sector; and education is the key to innovation, Eagar asserts.

This paper provides a way to visualize the extent of the displacement of manufacturing workers. It focuses on the Great Lakes states, where the job losses were particularly severe.

3.3 Methodology

The purpose of this paper is to present a powerful visualization of the dramatic job loss in manufacturing employment that has occurred in the Great Lakes region of the U.S. since 1997, following an expansion that had been greater than the national average until then. In addition, the ability to interpolate from surrounding values where data is missing, using a stochastic method, will be demonstrated. Kriged surface maps are constructed for 1990, 1997, and 2003 from employment levels across counties for five Great Lakes states: Illinois, Indiana, Michigan, Ohio, and Wisconsin. Kriging uses
statistical interpolation and smoothing techniques that enhance visualization of the variation in the occurrence of phenomena over geographic space.

3.3.1 Kriging

In order to visualize the growth and subsequent decline in manufacturing employment in the Great Lakes region of the U.S., I use a spatial interpolation technique that is known as kriging, developed to predict ore reserves for the mining industry in South Africa. Helsel and Troutt (2004) outlined the process of kriging that will be used for this analysis.

Kriging is named after Daniel G. Krige, a South African mining engineer who first documented and attempted to address significant shortcomings in the prevailing technique of estimating disseminated gold ore reserves as the average of a limited number of nearby core-sample assays around a block of ore to be stoped. His work paved the way for the formalization of the theory of regionalized variables by Georges Matheron in Paris, and the kriging methodology that is based on this theory (Krige, 1951; Matheron, 1962, 1963, 1965).

Regionalized variables are variables distributed in space (where space can be extended to include time, parameter space, property space, etc.). They are neither random nor deterministic. Unlike random variables, regional variables exhibit spatial continuity. On the other hand, their spatial component makes them so complex (such as when they are generated by multifarious natural, physical, or chemical processes that are either not well understood or too torturous to model quantitatively), that they cannot be described by any deterministic function either. Furthermore, even though regionalized variables are spatially continuous, not every location is sampled,
necessitating the estimation of unknown values from known values at specific locations
(Chambers et al., 2000; Isaaks and Srivastava, 1989). To resolve the uncertainty about
what happens at the unsampled locations, the kriging approach is to model the process
as a random function, such that the variable at a given location is a function of the same
variable but measured at different locations; the results can then be used for
interpolation and extrapolation (Agterberg, 1974; Cressie, 1986).

Goovaerts (1997, 1999) describes the steps involved in geostatistical analysis.
The first step in spatial statistics is often referred to as ESDA, exploratory spatial data
analysis. In kriging, this involves an examination of the data collected as well as the
locations of the sample sites for spatial patterns. To model the data, including the
spatial component, we can denote a set of n observations as  \( z(u_a), a=1, 2, \ldots, n; \)
where  \( z \) represents the attribute of interest, and  \( u_a \) represents the vector of spatial coordinates
of the  \( a \)th observation. Spatial relations between data values could be displayed by
what are called  \( h \)-scattergrams, which plot all pairs of data  \( (z(u_a), z(u_a + h)) \) on the same
attribute  \( z \) at locations separated by a given distance  \( |h| \) with a magnitude  \( h \) in a
particular direction  \( \theta \). The magnitude of this distance is alternately referred to as
\textit{separation, bin, or lag}. By convention, the value at the start of the vector  \( h \),  \( z(u_a) \), is
called the \textit{tail value}, whereas the value at the end,  \( z(u_a + h) \), is the \textit{head value}.

The presence or absence of any increasing variability for data values farther
apart in space that may be suspected from visual inspection of the scattergrams can be
confirmed by calculation of the linear correlation coefficient between the head and tail
values for each class of distance and direction. This correlation coefficient is the unit-
free measure of the average similarity or spatial continuity between data separated by a
vector  \( h \) and is calculated as the standardized form of the covariance. Experimental
correlograms plot the estimated correlation coefficients as a function of the separation distance and direction. Correlograms describe the spatial pattern in terms of similarity or spatial continuity. The distance where the correlation approaches 0 is called the range or zone of influence of the attribute measurements.

While correlograms are used frequently in the European and South-African literature on kriging, U.S. authors seem to favor experimental variograms (or, more accurately, semivariograms), which plot a measure of the dissimilarity or increasing variability of the data as a function of distance. The experimental variogram is calculated as the sum of all data pairs within a particular distance, divided by twice the number of data pairs found for that distance (Goovaerts, 1997, 1998; Chambers, Yarus and Hird, 2000):

$$
\gamma(h) = \frac{\sum_{i=1}^{N(h)} [z(u_i) - z(u_i + h)]^2}{2N(h)}
$$

(1)

where \(N(h)\) is the number of data pairs within the class of data and direction. In other words, it is one half times the average of the squared differences between pairs of points spaced at a distance \(h\) (hence the prefix “semi” attached by purists), or the sum of the variances of two random variables from two locations minus twice the covariance.

Figure 3-3 is a graphical representation of a continuous theoretical variogram, which shows how the variance increases with distance (Fitz-Simons, 2003). The experimental variogram that is calculated from the data is a scatter plot that must be fitted to such a theoretical variogram. The terms used to describe the various aspects of the variogram reflect the kriging technique’s mining origin. The discontinuity that is found at the origin even when the distance between the two locations is zero is called the nugget. The nugget represents data variation due to measurement errors and/or
data variation at a micro-scale (in mining, random pockets of a mineral deposit are called nuggets). The distance beyond which the data do not have significant statistical dependence is called the range. The sill represents the total variation in the data at the point where the range is reached and the variance plateaus. The partial sill is the amount of small-scale variation.

![Theoretical variogram](image)

**Figure 3-10. Theoretical variogram.**

Experimental variograms are computed based on different directional orientations of the data pairs. This is done to check for anisotropy, or dependence on orientation. So long as the variograms in different directions are not significantly different from one another, the variability is said to be isotropic or omnidirectional. Anisotropy requires further diagnostics and investigation into the data and data structures to understand the reason; corrective measures may need to be taken. Modeling anisotropy requires functions that depend on the vector $h$ rather than the distance $h = |h|$; therefore, the theoretical models used for prediction must be adjusted
before predictions can be made. The type of correction depends on the origin of the
anisotropy (Goovaerts, 1997; Gringarten and Deutsch, 2001).

The experimental variogram forms the lynchpin of geostatistical analysis and
must be computed, interpreted, and modeled rigorously in order to obtain meaningful
results from the remaining analysis. Yet, the calculation of sample variograms is
anything but routine. For example, when data are not spaced regularly on a grid, it may
be difficult to find enough sample points that are separated by exactly the same lag
vector. Grouping may necessitate deciding on a lag tolerance and an angle tolerance.
There are many instances where the outcome is dependent on the researcher's
judgement. Experienced geostatisticians often publish their recommendations (Cressie
1991; Goovaerts 1997; Gringarten and Deutsch 2001). Some of the now generally
accepted “rules of thumb” include:

1. A variogram should not be computed for distances larger than half of the largest
dimension of the study area. In other words, the lag size times the number of
lags should not exceed one half of the largest distance among all points.

2. It is beneficial to experiment with different combinations of the number and width
of classes of distances, in order to find a balance between variograms that are
either too smooth or too noisy.

3. Extreme values can have a significant impact on the variogram, and make it
more difficult to interpret.

4. Data transformations and detrending to force Gaussian distributions of the data
will have a positive impact on the shape of the variogram. Without the
assumption of normally distributed data, it will be possible to identify areas where
the prediction uncertainty is large or small, but no further inferences concerning
the credibility of the predictions can be made. Any trends removed will have to be added back in, and data transformations require back-transformation of predicted values. In older software, until just a few years ago, these were difficult processes; the latest software, however, will perform these functions routinely.

(5) There is no one single way to compute semivariograms; the researcher should be guided by experience, knowledge of the data, and the objectives of the study.

The objective of spatial interpolation of the data is to predict the value of attribute z at an unsampled location \( u \), \( z(u) \), based on the values of z at n locations \( \{z(u_\alpha)\}, \alpha=1,\ldots,n \). Interpolation using deterministic techniques use mathematical functions. Kriging, on the other hand, uses both mathematical and statistical methods, so that the uncertainty of the predictions can be assessed. Some widely used deterministic approaches include:

(1) Tessellation of Thiessen or Voronoi polygons, where the estimated value equals the value of the closest observation (in essence, zones of influence of datapoints are defined);

(2) Inverse distance weighting, where the estimated value equals a linear combination of neighboring data;

(3) Method of splines, which fits a spline function (a set of polynomials of a given order) to the data, resulting in very smooth variation from one observation to the other.

These approaches share a number of drawbacks that make them less suitable to the interpolation of spatial data than the probabilistic method used in kriging. In particular, they do not take into account any patterns of spatial continuity that may be present in the data, nor do they account for the support or size over which the data is
measured, and the consequences of any changes in support. Most importantly, a deterministic model assigns to any unsampled location \( u \) a single estimated value \( z^*(u) \), assuming the potential error \( z^*(u) - z(u) \) to be negligible. This is justifiable only if the estimate \( z^*(u) \) is based on sufficient data or knowledge of the process governing the spatial distribution of attribute \( z \) (Goovaerts, 1997).

In contrast, probabilistic approaches provide a set of possible values for the unsampled location, together with the corresponding probabilities of occurrence. Instead of relying on the physics of the phenomenon, most of the information used in a probabilistic model comes from the data. However, deterministic and probabilistic models could complement one another. For example, a deterministic representation of better known large-scale structures could be combined with a probabilistic modeling of small-scale variability.

Kriging is based on the random function (RF) model, which sees the set of unknown values as a set of spatially dependent random variables. It models the *local* uncertainty about the unsampled attribute value at any location \( u \) as the set of possible realizations of the random variable at that location. In other words, an RF is a set of usually dependent random variables \( Z(u) \), one for each location \( u \) in the study area. The relationship between two random variables \( Z(u) \) and \( Z(u') \) is measured by the covariance:

\[
C(u, u') = E(Z(u) \cdot Z(u')) - E(Z(u)) \cdot E(Z(u'))
\]  

A property of the RF model is stationarity. Stationarity is needed for inference—it is not a characteristic of the phenomenon under study. Stationarity is a decision—it is not a hypothesis than can be proven or refuted from the data. An RF model is said to be
stationary of order one if the expected value \( E\{Z(u)\} \) exists and is invariant over the study area.

\[
m = E\{Z(u)\} \quad \forall u
\]  

Stationarity of order two requires that in addition the two-point covariance \( C(h) \) exists and depends only on the separation vector \( h \):

\[
C(h) = E\{Z(u)Z(u+h)\} - m^2
\]  

For a stationary RF:

\[
\gamma(h) = C(0) - C(h) \\
\rho(h) = 1 - \gamma(h)/C(0)
\]

Before actual prediction can begin, a continuous theoretical variogram model is fitted to the experimental variograms. The purpose is twofold: (1) to provide semivariogram values for any possible lag \( h \) required by prediction algorithms (such as Kriging), and (2) to smooth out sample fluctuations (Goovaerts 1998). As a consequence of the random function theory, the theoretical variogram models are subject to certain conditions; in particular, they must be such that the variance of any linear combination of random variables is non-negative. In practice, this means that only a limited number of continuous functions qualify.

Some commonly used basic models that are included in most of the geostatistical software include the nugget effect model (which assumes no spatial correlation), the spherical model with range \( a \) (which is bounded in that it reaches a sill at a given range), the exponential model with practical range \( a \) (where the practical range is defined as the distance at which the model value is at 95\% of the sill), the Gaussian model with practical range \( a \), and the power model (where \( g(h) = h^\omega \), with \( 0 < \omega < 2 \)). Figure 3-4 shows the three bounded models with the same range, and power
models for different values of \( \omega \). With these models, different sample variogram behaviors at either the origin (linear, quadratic) or at infinity (bounded, unbounded) can be modeled. In addition, any positive linear combination of permissible models is a permissible model.

Three prerequisites for successful modeling are: (1) reliable estimates for the variogram values (robust estimators, data transformation); (2) permissible semivariogram or covariance models; and (3) the use of ancillary information such as knowledge of the area and phenomenon under study. Goovaerts (1997) emphasizes the art of modeling, capitalizing on all sources of available information, to build a permissible model that captures the major spatial features (e.g., short-scale variability) of the attribute under study.

Goovaerts (1998) calls kriging "a generic name adopted by the geostatisticians for a family of generalized least-squares regression algorithms." Ordinary kriging (OK) estimates the value of an attribute at an unsampled location as the linear combination of the 10 to 20 closest neighboring observations.
\[ z^* (u) = \sum_{\alpha=1}^{N(u)} \lambda_{\alpha}(u) z(u_{\alpha}) \] (7)

where the weights \( \lambda_{\alpha} \) are such that the estimator is unbiased (ensured by constraining the weights to one) and the estimation variance is minimum.

3.3.2 Data and Units of Analysis

For this study, annualized employment counts were obtained from the U.S. Bureau of Labor Statistics (BLS) through its comprehensive Quarterly Census of Employment and Wages (QCEW), formerly known as the Covered Employment and Wages (CEW) program or ES-202. The QCEW program comprises those positions that are covered by state unemployment insurance laws. It measures employment by place of work, as opposed to place of residence, and may include multiple job holdings where they exist.

Counties are used as the primary spatial unit of analysis. The employment data cover county employment in the manufacturing sector for 1990, 1997, and 2003 in five contiguous Great Lakes states: Illinois, Indiana, Michigan, Ohio, and Wisconsin. The North American Industry Classification System (NAICS) codes are used at the 2-digit level to classify and aggregate the employment data as manufacturing (NAICS codes 31-33).\(^7\)

The Bureau of Labor Statistics withholds publication of UI-covered employment data for any industry level when necessary to protect the identity of cooperating

\(^7\) Prior to 2001, the ES-202 program used the Standard Industrial Classification (SIC) system. The data from 1990 and 1997 were reconstructed to conform to the 2002 version of the NAICS.
employers. As the level of disaggregation increases, so does the incidence of missing data. Even at the 2-digit NAICS county level, several observations were not disclosed.

ArcGIS 9.1 and its Geostatistical Analyst extension are used to perform the kriging on this data.

3.4 Discussion of Results

Because of the need to protect the privacy of individual establishments, publicly available employment and other economic data are often aggregated to a sufficient extent to prevent the disclosure or reconstruction of the firms involved. Disaggregated datasets include sometimes large numbers of missing observations. Researchers are thus forced to choose between a coarser level of aggregation that masks much of the salient detail, or to use data at a finer level of disaggregation without knowledge of the effect of missing observations on the outcome.

The use of kriging to interpolate missing data has the advantage over other, deterministic interpolation methods of allowing the researcher to incorporate an explicit statistical model that produces a prediction surface with the lowest errors based on the relationship between distance and value. In addition, as a surface model, kriging smoothes the data over space, thereby enhancing visualization of changes in economic data over a geographic area and over time. These concepts are illustrated using employment data for the Great Lakes region for the period 1990-2003. Figure 3-5 shows a traditional choropleth map of the observed county manufacturing employment data in the 5-state Great Lakes region for 2003.
Since kriging is performed on point data, counties are referenced by their centroids (or seats). Thus, the actual spatial support (the size and shape of the county), is ignored, and it is assumed that the county employment is concentrated on this one point. This is a somewhat unsatisfactory assumption if the counties are very different in size and shape. For the region under study, however, the counties are fairly homogenous.

Exploratory data analysis reveals that for all three years of data (1990, 1997, and 2003), a Gaussian distribution can be forced by lognormal transformation of the data. In addition, the trend analysis tool that is part of ESRI's ArcGIS Geostatistical Analyst
extension identified large-scale variation in the data, usually referred to as a global trend. In other words, the mean data value is not stationary over the extent of the data. The trend was removed from the data and represented by a second-order polynomial. Thus, the kriging is performed only on the residuals, or the short-range variation component of the surface. Before the final surface is created, the trend is added back in so that the predictions are meaningful and more accurate. Removal of the trend means that the variography is not influenced by large-scale variations. Figure 3-6 shows the experimental semivariogram for the 2003 data, transformed and detrended, that was fitted to a spherical theoretical model. No significant anisotropy was found.

![Figure 3-6. Fitted semivariogram for 2003 employment data.](image)

The spherical model was decided on based on results of cross-validations, conducted to evaluate the predictions before the final model is fitted. Cross-validation systematically goes through the data, omitting one data point at a time and predicting its value using the rest of the data. The predicted value is then compared to the actual value. The calculated statistics allow for model comparison to find the one that is the most reasonable for map production.
For the data in this study, Table 3-2 presents the cross-validation results of the final models chosen. A model that is unbiased (that is, centered on the measurement values) and which provides accurate predictions, would have a mean prediction error close to zero. However, since the employment data have a very wide scale, a more meaningful measurement is probably the mean standardized prediction error, which should also be close to zero. The mean standardized prediction error is obtained by dividing the prediction errors by their prediction standard errors.

**Table 3-2. Cross-validation results**

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>2.008</td>
<td>-354.4</td>
<td>-546.4</td>
</tr>
<tr>
<td>Root Mean Square</td>
<td>16460</td>
<td>22300</td>
<td>24960</td>
</tr>
<tr>
<td>Average Standard Error</td>
<td>23500</td>
<td>26460</td>
<td>27460</td>
</tr>
<tr>
<td>Mean Standardized</td>
<td>-0.006989</td>
<td>-0.01504</td>
<td>-0.03553</td>
</tr>
<tr>
<td>Root-Mean-Square-Standardized</td>
<td>0.8158</td>
<td>0.9211</td>
<td>1.101</td>
</tr>
</tbody>
</table>

The root-mean-square prediction errors measure how close the predictions are to the measurement values. When choosing between competing models, lower root-mean-square errors are preferred. Furthermore, the cross-validation results provide an indication of the validity of the prediction standard errors. The root-mean-square-standardized prediction errors are calculated by dividing the errors by the estimated standard errors. Thus, a value of the root-mean-square-standardized prediction error close to 1 indicates that the standard errors are accurate.

Figure 3-7 shows the prediction maps for 1990, 1997, and 2003. Prior to 1997, the gain in manufacturing jobs seen in the U.S. is particularly evident in Indiana, Michigan, and Wisconsin. Ohio, on the other hand, did not benefit from this expansion.
On the kriged surface maps, this is evident from a widening of the color bands, and a general deepening of the color ramp. Between 1997 and 2003, a general decline is noted in all five states, down to levels smaller than in 1990. All the color bands are reduced in size, and the entire map is lighter.

![Kriged maps of manufacturing employment in the Great Lakes region](image)

**Figure 3-7.** Kriged maps of manufacturing employment in the Great Lakes region.

### 3. 4. 1 Conclusion

are shown in a number of well-organized tables and bar graphs. The methodology introduced in this paper is certainly not a substitute for such an analysis. Rather, it represents a practical complement to the investigation and adds a visually appealing means of reporting the results. Tables and bar graphs require aggregation of the data; for example, comparing metropolitan statistical areas within a state, or comparing states to each other. Listings of metropolitan areas lose in their ability to have the reader see the geographic context. Surface maps, on the other hand, allow county data to be shown visually, even over large geographic areas.

Increases and decreases in county employment could be depicted in choropleth maps. Choropleth maps classify the attribute data in categories, and each category is shown on the map either with a different color or with a different pattern. However, because of the artificial boundaries of the political units for which data is represented, they have a somewhat “cluttered” appearance, which detracts from their ability to show changes over time. In addition, as in Figure 3-5, they show the missing observations where data is suppressed or not available.

Deterministic or first-order interpolation produces surface maps that improve on the choropleth map by providing some smoothing and estimates for the missing values. However, the purely mathematical functions used to produce these maps may limit their usefulness. Some of these maps, such as those produced by Thiessen tessellation, require a certain familiarity with the method before they can be interpreted. Others, such as those produced by inverse distance weighting, replace actual values with interpolated values, without confidence intervals. Yet others, such as maps produced with spline methods, may produce interpolated results that, due to mathematical artifact, are difficult to interpret economically, such as negative employment values.
Kriged maps, too, have their limitations. Most significantly, they tend to be as good or as bad as the researcher that produces them. With current advances in software, it is tempting to push a few buttons and enjoy rapidly displayed results that are meaningless. On the other hand, kriged maps can provide a powerful visualization of a large amount of data that may otherwise be difficult to interpret. Particularly when combined with electronic multimedia, the smoothed interpolated maps can be used to picture the spatial-temporal nature of large datasets. This can only enhance how data are interpreted by manufacturers, planners, and policy makers. Moreover, standard statistical techniques are used to analyze the validity of the results.

3.5 Works Cited


4.1 Introduction

There is increasing concern that the dramatic expansion of the services sector during the post-war period, particularly in the share of total labor employed, poses a threat to the nation’s economic strength and standard of living. During the last five decades the U.S. has seen a steady decline in manufacturing employment as a share of total employment, a phenomenon often referred to as deindustrialization. Data from the Bureau of Labor Statistics indicate that manufacturing’s share of employment fell from more than 25 per cent in 1960 to less than 13 per cent in 2003 and continues to shrink, with over half of the decline occurring after 1980. Between 1997 and 2003, the manufacturing sector lost more than 3 million jobs, a decrease of 16.7 per cent, and the level of manufacturing employment is now at its lowest point since 1958 (Bivens 2004). In contrast, employment in the services sector increased by 13.2 per cent during the same period, and by 17.9 per cent from 1990 to 1997. Services employment accounted for about 56 per cent of total employment in 1960 and grew to about 73 per cent in 1994. According to Rowthorn and Ramaswamy (1997), no other advanced economy has a higher services employment share.

Table 4-1 provides an overview of the long-run trends in manufacturing compared to other industry classifications into which the economy is usually divided for
analytical purposes (Schiller and Trebing 2003). Besides manufacturing’s declining share in total (non-agricultural) employment, there has been a corresponding decline in manufacturing’s share of nominal GDP (that is, GDP measured in current dollars, not adjusted for inflation) from 28.6 per cent in 1950 to 15.5 per cent in 2000.

Table 4-1. Sector shares in nominal GDP and in nonagricultural employment. Source: Schiller and Trebing (2003).

<table>
<thead>
<tr>
<th>Sector</th>
<th>GDP Shares, Current $, %</th>
<th>Nonagricultural Employment Shares, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Services</td>
<td>8.2</td>
<td>21.5</td>
</tr>
<tr>
<td>Finance, insurance, and real estate</td>
<td>10.5</td>
<td>20.1</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>28.6</td>
<td>15.5</td>
</tr>
<tr>
<td>Government</td>
<td>10.8</td>
<td>12.4</td>
</tr>
<tr>
<td>Retail trade</td>
<td>10.8</td>
<td>9.0</td>
</tr>
<tr>
<td>Transportation and public utilities</td>
<td>9.1</td>
<td>8.2</td>
</tr>
<tr>
<td>Wholesale trade</td>
<td>6.7</td>
<td>7.1</td>
</tr>
<tr>
<td>Construction</td>
<td>4.5</td>
<td>4.7</td>
</tr>
<tr>
<td>Agriculture, forestry, and fishing</td>
<td>7.0</td>
<td>1.4</td>
</tr>
<tr>
<td>Mining</td>
<td>3.7</td>
<td>1.4</td>
</tr>
</tbody>
</table>

Apprehension about a dwindling U.S. industrial base has resulted in a renewed push for public policy initiatives. A doubling of trade imports (by dollar value) into the U.S. since 1990 fuels fear that the U.S. domination of world markets for manufactured goods is coming to an end. As domestic producers face increased global competitive pressures, innovation is recognized as the major source of sustained competitive advantage (Porter, 1998). Youtie et al. (2003) reason that “companies that adopt innovative products, processes, or organizational methods can distinguish themselves
from other companies and grow, even faced with low-cost competition.” This provides both an opportunity and a challenge for policy makers to encourage manufacturers, especially smaller established firms, to focus on innovation. Shapiro et al. (2005) estimate that 98 per cent of all manufacturers, or approximately 350,000 enterprises, employ 500 or fewer employees each. More than half of the value of U.S. industrial production is supplied by these small to mid-sized manufacturing firms, which provide about 10 million jobs or two-thirds of all U.S. manufacturing employment. Cooperative public-private technology transfer programs play an increasingly important role in supporting and promoting innovation. For example, from 1992 to 1994, $1 billion in combined public funding supported technology policy and technology transfer partnerships between private and public organizations in all 50 states. In 1994, $3.1 billion was spent by 10 federal agencies (Shapira and Youtie 1996). Recently, however, Congress has eliminated or reduced many programs. Even so, more than half of U.S. research and development – over $60 billion – is funded by the federal government.

Bivens (2004) calls for a different kind of policy initiatives: dollar relief and trade relief. He considers the rapid decline of U.S. manufacturing “a policy-induced crisis that warrants policy solutions.” First and foremost he blames the overvalued U.S. dollar. When a currency is overvalued, that country’s exports become more expensive to foreign buyers, while imports become less expensive to domestic buyers. With U.S. products uncompetitive in the world market, the overall trade deficit (the difference between the volume of a nation’s exports and imports) rose by $411 billion between 1995 and 2004. Manufactured goods accounted for $408 billion of that increase. By the end of 2002, the manufacturing trade deficit stood at $491 billion, which means that $491 billion of domestic demand for manufactured goods is supplied by foreign
producers and does not translate into increased domestic production and employment. Bivens estimates that balancing the trade account of the U.S. may translate into an employment gain as high as 3.6 million jobs.

Why should policy-makers be alarmed about the hollowing-out of the manufacturing sector? At issue is a growing concern that a structural change of the economy toward services will cause a serious decline in our standard of living. This fear is premised on the notion that manufacturing matters; that it is the manufacturing sector, not the services sector, which drives economic growth. For example, a study commissioned by the Council of Manufacturing Associations contends that “manufacturing spawns more additional economic activity and related jobs than does any other economic sector” and that “America’s unprecedented wealth and world economic leadership are made possible by a critical mass of manufacturing” (Popkin 2003).

Eagar (2003) agrees. “To live well, a nation must produce well,” he states, adding, “Manufacturing is critical to the U.S. economy because it not only provides new sources of employment, but in the automotive sector it provides over 6 ‘spin-off’ jobs for every direct labor job.” According to Eagar (2003), the only wealth-producing economic sectors are agriculture, mining, manufacturing, and construction; other sectors such as services and trade can only redistribute that wealth. Furthermore, unlike agriculture and mining, manufacturing is not directly limited by natural resources, and unlike construction, manufactured products are easily exported. Bivens (2004) adds that manufacturing has historically been a primary source for middle-class jobs. With still over 70% of the work force without a college degree, manufacturing jobs pay well and provide sizeable benefits. Both Eagar (2003) and Bivens (2004) cite the high
productivity growth in the manufacturing sector as a driver of increases in national living standards.

The link between a strong manufacturing sector and rising national living standards has a theoretical foundation that dates back to the late 1960s. In 1966, Cambridge economist Nicholas Kaldor proposed three sets of general economic observations, usually referred to as Kaldor’s laws, which identify the manufacturing sector as the engine of economic growth (Kaldor 1966). However, these laws did not agree with the mainstream theories on economic growth. In particular, they collided with the neoclassical growth theory for which Solow later won a Nobel prize (Solow, 1956). Consequently, acceptance was slow. Recently, however, there has been a growing fascination with new endogenous growth theories, spearheaded by Romer (1986, 1990). Their emphasis on increasing marginal productivity and endogenous technological change has also rekindled research interest in Kaldor’s laws, since Kaldor was really the first post-war theorist to consider these phenomena.

Is manufacturing the engine that drives economic prosperity? Is an expansion of the services sector detrimental to economic growth? For example, Kaldor’s first law holds that economies with high growth in manufacturing experience higher economic growth than economies in which the manufacturing sector grows more slowly. Does this law imply that an expanding services sector, by reducing the role of manufacturing in the economy, reduces the rate of economic growth? Few studies have looked directly at the flip-side of the coin: the possible adverse effects of an expanding services sector. Do Kaldor’s laws apply to sub-national regions? While there is substantial research testing the validity of Kaldor’s laws as they apply to countries, especially in recent years, only a few have used sub-national data. To determine if manufacturing matters for regional
growth within the U.S., this paper explores the links between manufacturing, services, and output growth for U.S. states. First, Section 2 contrasts the neoclassical model of economic growth to Kaldor’s laws, and reviews some of the empirical literature on the subject. Section 3 discusses the methodology used to investigate if manufacturing is, indeed, the engine that drives economic growth for U.S. states, and if an expansion in the services sector reduces that growth. The results will be discussed in Section 4.

4.2 Review of the Theories of Economic Growth and Empirics

4.2.1 Kaldor’s Laws versus Neoclassical Growth Theory

Economic growth is most often analyzed within the framework of a theory known as the neoclassical growth model, which holds that aggregate output per person will continue to grow only so long as technological changes give rise to a level of savings and investment such that capital per unit of labor grows. In its simplest form, this model links aggregate output for the economy (Y) to three major inputs – labor (L), capital (K), and technology. The resulting production function may be converted to one that models output per unit of labor or per worker (Y/L) as a function of capital per worker (K/L) and technology (Bernat 2001). Figure 4-1 shows such a per worker production function, which initially holds technology constant. Underlying this model is the concept of diminishing returns to capital. Thus, equal increases in capital per unit of labor result in ever-decreasing increases in output per unit of labor (Hubbard and O’Brien, 2006).
Figure 4-1. Per-worker production function.

For example, amid bafflement, concern, and reluctant admiration for the speed with which some hitherto backward Asian economies had transformed themselves into “Asian Tigers,” Krugman (1994) predicted that their spectacular rates of economic growth are unsustainable and will have to slow over time. He pointed out that these newly industrializing countries achieved their rapid rate of growth through an astonishing mobilization of resources. High domestic savings rates (as high as 40 per cent in Singapore, for example) permit high rates of capital growth. However, in the neoclassical growth framework there are diminishing returns to factors of production. If the capital-to-labor ratio increases because the labor force does not grow as fast as capital, the marginal product of capital will fall. Thus, unless investment increases further, enough to offset the decline in the marginal product of capital, the growth of output will fall. Since it is unlikely that these Asian countries can increase their savings
and investment beyond their current high rates, so Krugman (1994) argues, a slowdown in their growth rates is inevitable.

With diminishing returns to capital, economic growth can be sustained only with advances in technology. Figure 4-2 shows the effect of technological changes on the per-worker production function (Hubbard and O’Brien, 2006). Even without changes in capital per unit of labor, output per worker is increased. Technological change is assumed to be exogenous in neoclassical growth theory; that is, the rate of technological change influences the rate of economic growth, but not vice versa. Chance discoveries and innovations afford firms new opportunities for profit, expansion, and new start-ups. Competition insures that these new technologies are adopted and exploited by all firms as long as they have perfect information about their existence. Increases in saving and investment will propel the economy to even further levels of prosperity and growth. However, unless technology keeps advancing, the prosperity may last, but the growth will not. Diminishing returns see to that.

![Figure 4-2. Technological change increases output per unit of labor.](image)
Under these conditions, differences in aggregate output between economies should disappear over time, a phenomenon referred to as convergence. First, any given increase in the K/L ratio will raise Y/L more in economies that start out with low levels of capital than in economies that start out with higher levels of capital. Second, economies with lower initial levels of capital tend to have higher investment rates because the rate of return tends to be higher. Furthermore, convergence is expedited by the mobility of both capital and labor (Bernat 2001).

However, there is little empirical evidence that convergence is taking place. For example, McGrattan and Schmitz (1999) show that “disparity in incomes is large and has grown over time, that there is no correlation between income levels and subsequent growth rates, that growth rate differences are large across countries and across time, and that the highest growth rates are now much higher than those 100 years ago.” To some, this is due to oversimplification of the model. Proponents of “conditional convergence” posit that convergence is conditioned on a “social infrastructure” of institutionalized characteristics of an economy, such as its political system, culture, and educational system. To others, the neoclassical growth is flawed (Bernat 2001).

Nicholas Kaldor (1908-1986), a prominent post-war neo-Keynesian economic theorist and an unrelenting critic of mainstream economics (i.e., economic theories based on a framework of general equilibrium), took issue with the neoclassical growth model in particular (Wulwick, 1993). It was Kaldor who first singled out manufacturing, the economic sector responsible for producing tangible “things” rather than intangible services, as the driving force behind long-run economic growth. Kaldor held a number of prestigious posts in Europe and served as an economic advisor to various governments.
He met with and was held in high esteem by the most notable economists of his time (among whom Keynes, Galbraith, Schumpeter, Pigou, Hicks, Friedman, Solow, and Samuelson). Yet, partly because of the political positions he held, his views were, at the time, considered controversial. In fact, Wulwick (1993) mentions that his Cambridge inaugural lecture received a great deal more publicity than such lectures usually do, since the media were able to attribute a recently enacted notorious selective employment tax scheme to him. Certainly, his theories on how output growth occurs and the role of the manufacturing sector as the engine that propels this growth were not received with immediate unequivocal support (Pasenetti 1983; Targetti 1992).

Kaldor frequently and strongly expressed his disenchantment with neoclassical growth theory, and argued that, in contrast to the neoclassical model's diminishing-returns aggregate production function, there are increasing returns to scale in the manufacturing sector (an idea going back to Allyn Young, of whom Kaldor was a student at the London School of Economics). The reasons for this are threefold: (1) endogenous technological change, in that there is new technology embodied in investment; (2) the process of "learning by doing"; and (3) external economies of scale, stemming from the discovery of new processes, from increasing differentiation, or from new subsidiary industries, not just from the expansion of a particular firm or industry (Targetti 1992).

Fond of the term "law" to refer to a body of broad and regularly recurring observations just as a natural scientist might, Kaldor used regression analysis to estimate the elasticity of labor productivity with respect to output growth in the manufacturing sector, and named his result Verdoorn's Law. In the Kaldorian

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8P. J. Verdoorn, an economist at the Dutch Central Planning Bureau, worked with Kaldor when Kaldor was director of research and planning for the Economic Commission for Europe (Wulwick, 1993). Verdoorn's work on the relationship between industrial productivity growth and
framework, the faster the rate of growth of output in manufacturing, the faster the rate of productivity growth in manufacturing. Then, since a growing manufacturing sector draws labor from other sectors with surplus labor (where the marginal product of labor is zero), productivity will rise in those sectors, leading to an increase in overall productivity in the economy (Chatterji and Wickens, 1983).

Kaldor’s explanation of economic growth has its roots in the theory of cumulative causation, or self-reinforcing cycles of success (or failure) in international competition: the rate of overall economic growth depends on the growth rate of output in the manufacturing sector, which in turn requires a high growth rate in exports; for exports to grow, the manufacturing sector must be competitive; and for the manufacturing sector to be competitive, it must have a high growth rate (Fingleton and McCombie, 1998). In contrast with the neoclassical model, where economic growth results from and is constrained by exogenous increases in the factors of production (labor and capital) and exogenous technological advancement, in the Kaldorian world growth is “induced by demand and not limited by resources” (Targetti 1992, p. 173).

Kaldor first articulated these principles in his 1966 inaugural lecture at Cambridge, in the context of explaining the differences in growth rates between twelve leading industrialized countries, “Causes of the Slow Rate of Economic Growth in the United Kingdom” (Kaldor, 1966). Based on empirical generalizations from his analysis of these countries’ economic performance between 1954 and 1964, Kaldor’s notion that manufacturing drives economic growth is summarized in the following three postulates, known as Kaldor’s laws:

---

industrial output was published in a relatively unknown Italian journal (Verdoorn, 1949). It received little attention until Kaldor discussed it in his 1966 inaugural address at Cambridge University (Kaldor, 1966).
(1) Kaldor's first law – the law of the manufacturing sector as the engine of growth:

There exists a strong relation between the growth of manufacturing output and the growth of GDP.

(2) Kaldor's second law–the Kaldor-Verdoorn law:

There is a strong positive relation between the rate of growth of productivity in manufacturing industry and the growth of manufacturing output.

(3) Kaldor's third law–the law of labor migration:

The faster the growth of manufacturing output, the faster the rate of labor transference from non-manufacturing to manufacturing, so that overall productivity growth is positively related to the growth of output and employment in manufacturing and negatively associated with the growth of employment outside manufacturing (Thirlwall 1983).

The first law makes clear the basic idea: it is the growth rate of the manufacturing sector that determines the economy's overall growth rate, because industrial growth is not just a shift of resources from one use to another, but a net increment in resources. Capital resources are produced, but what about labor? The third law is a presupposition of the first law: industrial labor has no opportunity cost outside the manufacturing sector because of surplus labor in the other sectors (agriculture and services). The second law says that there are increasing returns in the manufacturing sector; this law supports the first law but is not necessary (Thirlwall 1983).

Kaldor's laws are based on his econometric analysis on a cross-section of 12 countries (Japan, Italy, West Germany, Austria, France, Denmark, The Netherlands, Belgium, Norway, Canada, U.K., and U.S.) over the period 1952-54 to 1963-64. The bivariate regression models were simple. In keeping with what was customary for policy-oriented research at the time, Kaldor reported only the standard error of the regression coefficient, without further inference estimation (Wulwick, 1993). As his first
law, he found a strong correlation between the rate of economic growth \((g)\) and the growth rate of the manufacturing sector of the economy \((g_m)\):

\[
g = 1.153 + 0.614 (g_m) \quad R^2 = 0.959
\]  

\( (.040) \)  

From this equation it can be shown, by setting the overall growth rate equal to the growth rate in manufacturing, that economic growth rates of 3\% or more can be achieved only if the growth rate in the manufacturing sector is greater than the overall growth rate; the greater the excess of manufacturing growth over overall growth, the faster the economy will grow.

Kaldor's second law is based on the following relationship:

\[
p_m = 1.035 + 0.484 (g_m) \quad R^2 = 0.826
\]  

\( (.070) \)

where \(p_m\) stands for the rate of growth of productivity in manufacturing. This empirical relationship between productivity growth and output growth in manufacturing is also known as Verdoorn's Law, and the coefficient as the Verdoorn coefficient. Equation 2 implies that the manufacturing sector has an autonomous rate of productivity growth of approximately 1\% per cent. More importantly, however, every 1 per cent increase in manufacturing output increases its productivity by about one half per cent. This is a strong argument for endogenous technological change and learning by doing.

Letting \(e_m\) represent employment growth in manufacturing, and realizing that \(g_m = p_m + e_m\), Kaldor's estimation of \(e_m\) is a restatement of the Verdoorn relationship:

\[
e_m = -1.028 + 0.516 (g_m) \quad R^2 = 0.844
\]  

\( (.070) \)
The value of this coefficient of about .5 implies that an increase in manufacturing output of 1 percentage point induces an increase in manufacturing employment growth of about one half of 1 percentage point, and a one half of 1 percentage point increase in the growth of manufacturing productivity. This suggests that as manufacturing output grows, the increase in employment in the manufacturing sector is less than proportionate due to the growth in productivity – i.e., evidence of increasing returns to scale.

Kaldor modeled his third law as follows:

\[ p = 2.899 + 0.821 \, e_m - 1.183 \, e_{nm} \quad R^2 = 0.842 \]  

\[ (0.169) \quad (0.367) \]  

where \( e_{nm} \) is the growth of employment outside manufacturing (Thirlwall 1983). This relationship suggests that an economy's productivity growth is the result of increases in the manufacturing sector, while increases in other sectors have a negative effect on productivity. Kaldor stated the third law in terms of labor transference from sectors with low labor productivity (such as agriculture and mining) to manufacturing, which on the face of it seems to limit its applicability to economies in early stages of development.

However, Bernat (1996) points out that there is every reason to believe that this law also applies to developed economies such as the U.S., in spite of its declining manufacturing sector and its increasing services sector. This is because, first, not all regions within the U.S. have a declining manufacturing sector, and second, growth in manufacturing may induce productivity growth in other sectors that are closely linked to manufacturing.

4.2.2 Empirical Evidence

Early empirical support for Kaldor’s laws has been mixed (cf. Cripps and Tarling, 1973; Rowthorn 1975; Parikh 1978; among others). Most of the criticism has centered
on the Kaldor specification of Verdoorn’s law and the robustness of his estimates. Kaldor himself published revised specifications to correct for various problems (e.g., Kaldor 1968). In “A Plain Man’s Guide to Kaldor,” Thirlwall (1983) synthesizes Kaldor’s earliest propositions with later retractions and corrections, which Kaldor made in response to charges of model misspecification.

In spite of these controversial results, the Verdoorn/Kaldor position on increasing returns and external economies has found support among researchers such as Blitch (1983), who admonishes his readers that it is the purpose of economic science to describe and predict how an economy actually works, even if that means setting aside cherished paradigms. McCombie (1983), too, concludes that the evidence suggesting increasing returns to scale is significant and that continued support for a constant-returns model would indicate a pragmatic attempt to avoid the theoretical complexities inherent in an economies-of-scale model.

In recent years, there has been renewed interest in the role of manufacturing in economic growth. A number of empirical studies have found evidence of Kaldor’s laws in a variety of countries and international regions (cf. Hansen and Zhang, 1996; Felipe 1998; Fingleton and McCombie, 1998; Mamgain 1999; Pons-Novell and Viladecans-Marsal, 1999; Millin and Nichola, 2005). On the other hand, a report on the role of manufacturing industries by the Economics and Statistics Administration’s Office of Policy Development (U.S. Department of Commerce, 1995) points out that the United States, Germany, the United Kingdom, and Canada all have achieved “respectable” rates of overall growth, even though manufacturing grew less than GDP and manufacturing employment decreased. These conclusions contradict the results reported above.
McCombie and de Ridder (1983) are the first to test Kaldor’s laws on subnational data, using U.S. states as the geographic level of analysis. They conclude that generally their results either support or at least do not contradict Kaldor’s laws. Disaggregation of the data to state-level has some useful features in terms of model specification. One advantage is the reduction in socioeconomic differences between state populations (compared to international data), reducing the likelihood of specification errors. Bernat (1996) also uses cross-sectional state-level data. To test if Kaldor’s laws hold for the U.S. during the 1980s, he employs the same model specifications as McCombie and DeRidder (1983), but extends the sample from the largest 20 states to 49 states. Bernat’s findings clearly support Kaldor’s contention that manufacturing constitutes the engine of economic growth, and that output growth and manufacturing productivity are positively related. There is limited evidence of a relationship between productivity growth in manufacturing and productivity growth in the rest of the economy.

An important corollary contribution of Bernat’s paper is its application and economic interpretation of spatial econometric techniques to detect statistically significant clustering in the geographic distribution of the dataset. Gross state product growth rates originating in both the manufacturing and the services sectors showed evidence of spatial autocorrelation and heterogeneity. His spatial regimes analysis shows that there may be substantial variability in the relationship between manufacturing growth and economic growth. These findings have important implications for regional economic development and for the administration of appropriate public policies to spur the economic growth of lagging regions.
Among the few researchers who have examined the relationship between the growth of the services sector and growth of total output are Dutt and Lee (1993) and Wilber (2002). Dutt and Lee (1993) use cross-section data for a large set of countries from all continents, spanning the 1960s, 1970s, and 1980s, to determine if an increase in services-sector employment has a positive or negative impact on economic growth. They determine that there is evidence of an impact that is usually negative, even though the outcome appears to be sensitive to how the role of the services sector is measured. Wilber (2002) makes a distinction between the effect of an expansion in producer services and other types of services. Using panel data of OECD countries, he concludes that while a relative increase of the services sector as a whole has a negative effect on economic growth, producer services appear to have a positive impact. Wilber’s estimations include robust Feasible GLS specifications with cross-section weights, assuming that the variances of the residuals vary across countries. However, unlike Bernat (1996), no attempt is made to interpret any spatial dependence in the data in economic terms.

This paper extends the existing literature by examining the differential impact of manufacturing and services on economic growth for the U.S., using state-level data, taking into account any spatial autocorrelation and heterogeneity in the dataset.

4.3 Methodology

4.3.1 Spatial Econometrics

One of the reasons that previous studies testing Kaldor’s Laws did not always result in “good fits” may have been the presence of spatial autocorrelation (Bernat, 1996). Like serial autocorrelation in time series data, the presence of spatial
autocorrelation in cross-sectional data can bias statistical estimators and/or invalidate statistical inferences. Spatial autocorrelation is present in the model when the error terms in the regression model tend to be correlated among contiguous states. This could be the result of omitted variables, where the error terms pick up these variables which tend to be correlated in the same geographic area. This may occur because states are not necessarily functional economic areas. Alternatively, the value of the dependent variable in one state may be directly affected by the value of the dependent variable in neighboring states, independent of the effects of the exogenous variables (Maddala 2001; Bernat 1996). Therefore, in addition to estimating Kaldor’s laws based on the models described above, spatial autocorrelation should be tested for and spatial econometric models estimated when necessary.

Both types of spatial autocorrelation are modeled in Bernat’s (1996) study. The spatial lag model, which implies that the value of the dependent variable in one state is directly affected by the value of the dependent variable in neighboring states (also called substantive spatial autocorrelation), can be written as follows:

\[ y = \rho W_y + \beta X + \varepsilon \]  

or, in reduced form:

\[ y = (I - \rho W)^{-1} X \beta + (I - \rho W)^{-1} \varepsilon \]  

where \( y \) is the vector of dependent variables, \( \rho \) is the autoregressive coefficient, \( W_y \) is a contacts matrix of interactions, distances, or spatial weights, \( \beta \) is the vector of coefficients for the \( X \) matrix of independent variables, and \( \varepsilon \) is the vector of error terms (Anselin 2001). If \( \rho \) is significant at a value of, say, 0.5, and the dependent variable were the output growth in a given state, this would mean that this state’s output growth would increase by half a percent for every one percent increase in the output growth of a
neighboring state, regardless of the independent variables contained in $X$. The larger the autoregressive coefficient $\rho$, the greater the spatial dependence. When $\rho$ is significant, states would have a substantial interest in the economic growth of their neighbors. In terms of the econometrics of the estimation model, leaving the contacts matrix $W$ out of the model when it should be there would constitute a specification error, which biases the estimated coefficients and renders any statistical inferences invalid.

The spatial error model takes on the following form:

$$y = \beta X + \epsilon,$$  \hspace{1cm} (7)

where

$$\epsilon = \lambda W \epsilon + \xi$$  \hspace{1cm} (8)

which, since $\epsilon = (I - \lambda W)^{-1} \xi$, is equivalent to

$$y = X \beta + (I - \lambda W)^{-1} \xi$$  \hspace{1cm} (9)

or

$$y = \lambda Wy + X \beta - \lambda WX \beta + \xi$$  \hspace{1cm} (10)

Here, the dependence in the error terms means that, again assuming $y$ represents the growth rate in GSP, a state’s growth depends on the growth rate in neighboring states only to the extent that neighboring states have growth rates greater or smaller than their “normal” growth rate as predicted by equation 7. Thus, one state’s growth rate will not affect neighboring states unless it is significantly different from the expected value (indicated by a large residual in equation 7). Econometrically, when spatial error dependence is ignored, the parameter estimates are inefficient so that any inferences will not be valid, but they are still unbiased.

The contacts matrix $W$ is an $N \times N$ matrix that defines who is a “neighbor”. How $W$ is defined determines the spatial dependence that is assumed to exist in the model.
Its form varies from application to application, and is ideally suggested by underlying theory. Figure 4-3 illustrates how a simple binary weights matrix may be constructed for 5 observations arranged in space. In this particular case, neighbors are areal units that share a common border (the “rook’s” case). For example, the observations in areas 1 and 2 have only each other as neighbors. This is reflected in the spatial weights matrix $W$ as a 1 in the first column of the second row, as well as in the second column of the first row. The remaining cells in the first two rows and columns are zeros. Alternatively, the “queen’s” case would have all areal units that share even one point as neighbors. In that case, area 2 would also be adjacent to area 3. Besides adjacency as a criterion to define who is a neighbor, another common measure is distance. This allows for the modeling of distance decay, in that the intensity of the interaction between two observations in space may deteriorate when they are farther apart (Lee and Wong, 2001). Other criteria, including economic measures, could be used.

![Figure 4-3. Construction of a binary spatial weights matrix: “rook’s” case.](image)

Bernat (1996), in the absence of a form put forth by theory, calculates three different matrices: (1) a first-order contiguity matrix, which assumes that spatial dependence is based on shared borders; (2) an inverse distance matrix, which
measures the distance between state centroids and assumes that dependence is inversely related to this distance; and (3) a squared inverse distance matrix, which implies that the dependence dies out much sooner than in (2).

Exploratory spatial data analysis (ESDA) must be conducted before any models are estimated in order to detect the presence of spatial dependence in the dataset. The most popular test statistic used to determine whether data are randomly distributed in space is Moran’s I, a weighted product-moment correlation coefficient. The weights reflect geographic proximity as described above. Under the null hypothesis of spatial independence among the observations, the baseline z-score for Moran’s I is 1.96 (Kelejian and Prucha, 1999). Another frequently-used test statistic for spatial autocorrelation is Geary’s Ratio. Geary’s Ratio is similar to Moran’s I, but here the cross-product term compares two neighboring values with each other directly, instead of with the mean (Lee and Wong, 2001).

Spatial heterogeneity can take the form of non-constant error variances (heteroskedasticity) or non-constant model coefficients (Anselin 2001). What is important is that the instability is spatial or geographic, and the location of the observations is crucial in determining the form of the instability. For example, spatial regimes or geographic subsets of the data could be specified where the model slope is different. Another consideration that should be kept in mind is that spatial autocorrelation and spatial heterogeneity often go hand in hand and may be observationally equivalent. This means that tests for heteroskedasticity may be misleading, and that spatial autocorrelation and spatial heterogeneity should never be considered in isolation from one another.
The models in this paper will initially be estimated by means of OLS. Doing so is equivalent to assuming that the spatial lag and spatial error coefficients are nil (\( \rho = \lambda = 0 \)). The models will then be tested for the presence of spatial relationships. If, based on the Moran I statistic, the null hypothesis of no spatial autocorrelation is rejected, LaGrange Multiplier (LM) tests will be conducted in order to be able to select the correct dependence pattern (Anselin 2001).

To test for an omitted spatial lag, under the null hypothesis of no spatial AR lag model, the test statistic is:

\[
LM_\rho = \frac{(\hat{\epsilon}^\prime W\hat{\epsilon} / \hat{\sigma}^2)^2}{NJ}
\]

with

\[
J = \frac{1}{N\hat{\sigma}^2} [(W\hat{\beta})' M (W\hat{\beta}) - T \hat{\sigma}^2]
\]

where \( M = I - X(X'X)^{-1}X' \), \( T \) is the trace of the matrix \((W' + W) W\), \( \hat{\sigma}^2 = \hat{\epsilon}' \hat{\epsilon} / N \), and \( \hat{\epsilon} = My \) are the OLS residuals.

Spatially autoregressive errors are tested by:

\[
LM_\epsilon = \frac{(\hat{\epsilon}^\prime W\hat{\epsilon} / \hat{\sigma}^2)^2}{T}
\]

with the null hypothesis of no spatial AR error model.

If either one of these tests is significant, the models will be estimated by maximum likelihood, including a spatially lagged dependent variable for the spatial lag model. If both tests are significant, more robust tests will be conducted:

\[
LM_\rho' = \frac{(\hat{\epsilon}^\prime Wy - \hat{\epsilon}^\prime W\hat{\epsilon} / \hat{\sigma}^2)^2}{NJ - T}
\]

and
The \( \text{LM}^*_l \) statistic tests for a spatially lagged dependent variable in the presence of a spatial AR error process; conversely, \( \text{LM}^*_2 \) looks for a spatial AR error process in the presence of a spatially lagged dependent variable. The specification that will be used will depend on which of these robust tests is more significant (Anselin 2001; Florax, Folmer, and Rey, 2003).

4.3.2 Data

States are used as the primary spatial unit of analysis. State-level Personal Income data for the years 1990 through 1996 have been obtained from the Bureau of Economic Analysis. Nominal levels are adjusted for inflation using the Consumer Price Index (annualized CPI-U, all items, 1982-1984=100). Average annual growth rates are calculated for each state as follows:

\[
g_{PI} = \frac{1}{n} \ln \left( \frac{PI_n}{PI_1} \right)
\]

(16)

where \( PI_n \) represents the value of real Personal Income in the last year, \( PI_1 \) represents the value of real Personal Income in the first year, and \( n \) represents the number of years in the period. A growth rate calculated in this manner is usually referred to as an exponential or continuously compounded growth rate. Data for earnings from manufacturing and services were downloaded from the same source, and growth rates calculated in the same manner as described above.

Annualized state-level employment counts have been obtained from the U.S. Bureau of Labor Statistics (BLS) through its comprehensive Quarterly Census of
Employment and Wages (QCEW), formerly known as the Covered Employment and Wages (CEW) program or ES-202. The QCEW program comprises those positions that are covered by state unemployment insurance laws. It measures employment by place of work, as opposed to place of residence, and may include multiple job holdings where they exist. The employment data cover total employment as well as employment for the manufacturing and service sectors in the 48 continental states and the District of Columbia for the period 1990-2006.

The North American Industry Classification System (NAICS)\textsuperscript{9} codes are used at the 2-digit level to classify and aggregate the data as either manufacturing (NAICS codes 31-33) or services (51: Information; 52-53: Financial activities; 54-56: Professional and business services; 61-62: Education and health services; 72: Accommodation and food services; 81: Other services).\textsuperscript{10}

The exploratory spatial data analysis and subsequent spatial econometric calculations are carried out using ArcGIS 9.1 (ESRI) and SpaceStat 1.91 (Terraseer) software.

4.3.3 Model Specification

Following Kaldor’s own estimation of his first law, which asserts that manufacturing is the engine of economic growth, the simplest specification would be to examine the relationship between the growth rate of real income originating in

\textsuperscript{9} Prior to 2001, the ES-202 program used the Standard Industrial Classification (SIC) system. The data from 1990 through 1997 were reconstructed to conform to the 2002 version of the NAICS.

\textsuperscript{10} Both the Bureau of Economic Analysis and the Bureau of Labor Statistics withhold publication of data for any industry level when necessary to protect the identity of cooperating firms. As a result, some data points were estimated through spatial interpolation.
manufacturing and the growth rate of real personal income for the state as a whole. However, this model is more than likely mis-specified. Manufacturing real income is a component of the state’s real income; therefore, it is to be expected that the growth rate in manufacturing is positively associated with the overall growth rate (Sheehey, 1990).

Bernat (1996) uses an expanded version of this model, based on McCombie and DeRidder (1987). He regresses state income from sources other than manufacturing, farming, and mining on growth in state income originating in each of these sectors. Both growth in income from farming and growth in income from manufacturing turned out to be significant. However, while this specification shows the multiplier effect that these income sources have on other sectors, it does not contrast manufacturing as an engine of economic growth with other sectors of the economy, specifically the services sector.

Keeping in mind that Kaldor’s first law implies that there must also be a positive association between the rate of growth of personal income and the excess of the rate of growth in the manufacturing sector over the rate of growth in the services sector, replacing the regressor with a differential growth rate will avoid any spurious correlation. Furthermore, as pointed out by Wilber (2002), additional information concerning the role of the services sector is provided when the differential growth rate is specified as the excess of a services sector expansion over manufacturing sector. The population growth rate is added since the primary determinant of a state’s personal income is its population, leading to the following equations which will be estimated in this study:

\[ g_{PI} = a_1 + b_1 (g_{services} - g_{manuf}) + c_1 g_{pop} \]  
\[ g_{PI} = a_2 + b_2 (e_{services} - e_{manuf}) + c_2 g_{pop} \]

where

\[ g_{PI} \] represents the average annual growth rate in real personal income;
\( g_{\text{services}} \) represents the average annual growth rate in real personal income originating in the services sector;

\( g_{\text{manuf}} \) represents the average annual growth rate in real personal income originating in the manufacturing sector;

\( g_{\text{pop}} \) represents the average annual growth rate of the population;

\( e_{\text{services}} \) represents the average annual growth rate in employment in the services sector; and

\( e_{\text{manuf}} \) represents the average annual growth rate in employment in the manufacturing sector.

### 4.4 Results

From the preliminary analysis of the Personal Income (PI) data used in this study, it is apparent that the 2001 recession has had a disproportionate effect on the manufacturing sector. As shown in Figures 4-4 and 4-5, whereas total PI, expressed in 2003 constant dollars, only leveled off and then took off again, PI originating in manufacturing declined sharply and has not yet recovered. Even so, it is still well above pre-1997 levels.
At the same time, however, manufacturing employment as a share of total employment has declined steadily over the entire study period. This is in sharp contrast to the services sector’s unremitting increase in employment share (see Figure 4-6).
Figure 4-6. U.S. sector employment as shares of total employment.

Figure 4-7 pictures the average annual rates of decline in manufacturing employment as a share of total employment for each state. Only two states, North Dakota and Nevada, have positive average annual growth rates, amounting to 1.68 per cent and 0.32 per cent respectively. The most rural of all states, with more than 90% of
the land area comprised of farms, North Dakota has a smaller manufacturing sector than most states. However, recently its manufacturing industries have grown considerably, especially food processing and farm equipment. Most of Nevada’s jobs are in traveler accommodation, but it has a “Made in Nevada” initiative designed to build demand for Nevada products and industries, while building connections between Nevada firms and industries. It is the only state for which the average growth in manufacturing jobs outstrips the average growth in services jobs, by about 0.5 per cent. Rhode Island had the greatest average rate of decline in its manufacturing employment share, at -4.6%. New Jersey, North Carolina, and Florida also had average rates of decline in excess of 4%. Ohio, on the other hand had a rate of decline right at the national average.

![Changes in Manufacturing Employment Shares 1990-2006](image)

**Note:** Growth rate represents the average annual percentage change in a state’s manufacturing employment as a share of its total employment.

**Figure 4-7. Changes in manufacturing employment shares, by state.**
While all states except North Dakota and Nevada have negative average annual growth rates in manufacturing employment as a share of total employment, not all states have negative annual growth rates in manufacturing employment levels. Ten states, in fact, have positive annual growth rates. That means that for eight of these states, the declining shares in manufacturing employment are strictly due to higher growth rates in other sectors.

In order to determine if there is a significant difference in PI growth between states that have declining manufacturing employment levels and states that have growing manufacturing employment levels, a t-test comparing means for independent samples is conducted. The results are shown in Table 4-2. From this test, it can be concluded, albeit with caution, that both the growth rate in real PI and the growth rate in real PI per capita are negatively impacted by declining manufacturing employment growth rates. The caution is in order since this test is based on random assignment to the grouping variable. Obviously, the positive and negative values of manufacturing employment growth rates are not random; therefore, the results of this test could mask the effect of other variables on the difference in real PI growth rates.

Table 4-2. Comparing means, independent samples

<table>
<thead>
<tr>
<th></th>
<th>Group</th>
<th>N</th>
<th>Mean</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Real PI growth rate</td>
<td>Manufacturing employment decline</td>
<td>38</td>
<td>2.3722</td>
<td>.73067</td>
</tr>
<tr>
<td></td>
<td>Manufacturing employment growth</td>
<td>10</td>
<td>2.9749</td>
<td>1.25610</td>
</tr>
<tr>
<td>Real PI per capita</td>
<td>Manufacturing employment decline</td>
<td>38</td>
<td>1.3231</td>
<td>.23692</td>
</tr>
<tr>
<td>growth rate</td>
<td>Manufacturing employment growth</td>
<td>10</td>
<td>1.5862</td>
<td>.32759</td>
</tr>
</tbody>
</table>
Average annual growth rates in per capita real PI for each state are shown in Figure 4-8. This map is an important preliminary tool in the exploratory spatial data analysis (ESDA) of the dependent variable in subsequent regressions. There appears to be significant local high-high spatial autocorrelation in the western states, and low-low spatial autocorrelation in the states surrounding the great lakes. California shows a potential low-high contrast, with a growth rate of only 2.25 per cent, surrounded by high-growth states and right next to Nevada with the highest growth rate in the country, 5.8 per cent.

<table>
<thead>
<tr>
<th></th>
<th>F</th>
<th>Sig.</th>
<th>t</th>
<th>df</th>
<th>Sig. (2-tailed)</th>
<th>Mean Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Real PI growth rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Equal variances assumed</td>
<td>.474</td>
<td>.495</td>
<td>-2.878</td>
<td>46</td>
<td>.006</td>
<td>-.263076</td>
</tr>
<tr>
<td>Equal variances not assumed</td>
<td>-2.381</td>
<td>11.595</td>
<td>.035</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Real PI per capita growth rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Equal variances assumed</td>
<td>4.241</td>
<td>.045</td>
<td>-1.974</td>
<td>46</td>
<td>.054</td>
<td>-.6027</td>
</tr>
<tr>
<td>Equal variances not assumed</td>
<td>-1.454</td>
<td>10.654</td>
<td>.175</td>
<td></td>
<td></td>
<td>-.6027</td>
</tr>
</tbody>
</table>
Figure 4-8. Average annual growth rates in real PI.

Estimation of the global Moran I statistic using a row-standardized spatial weights matrix with queen-contiguity yields a value of 0.5170 and is consistently pseudo-significant even with just 99 permutations. A random permutation method is used to compute the pseudo-significance. This procedure recalculates the statistic many times to generate a reference distribution. The computed pseudo-significance is sensitive to the number of permutations; the greater the number of permutations, the smaller the p-value. A significant Moran’s I statistic confirms the presence of spatial autocorrelation and/or heterogeneity; however, it does not provide further information about the nature of the spatial autocorrelation.
Figure 4-8 above suggests that local spatial autocorrelation may be present. Estimation of a Local Indicator of Spatial Autocorrelation (LISA) will confirm either clustering of the values for the variable under investigation (positive local spatial autocorrelation), or the presence of spatial outliers (negative local spatial autocorrelation). Clustering can be of either high or low values; spatial outliers can be either a low value amidst high values, or vice versa. In this case, the local Moran I confirms, with a p-value of 0.01, the presence of a cluster of low values by the Great Lakes and a cluster of high values in the West. The suspicion that California’s growth rate represents a low spatial outlier is also confirmed.

Table 4-3 shows the results of the initial OLS estimation of equations 17 and 18. The results show that growth in the services sector that exceeds manufacturing growth, as measured by real income, has a statistically significant detrimental effect on economic growth. The coefficient for the excess of employment growth in services is not significant. However, in light of the statistically significant Moran’s I statistic, indicating a problem with spatial autocorrelation, the model is more than likely mis-specified. The regression output shows a decent fit, with adjusted R$^2$ values in excess of 90 per cent. The multicollinearity condition numbers do not indicate a problem (typically, an indicator threshold of 30 is used as a rule-of-thumb). The Jarque-Bera test on normality of errors suggests a problem, especially for exact inference. The tests for heteroskedasticity (Breusch-Pagain, Koenker-Bassett, and White) are not significant. The LaGrange Multiplier (LM) statistic for spatial error is statistically significant, indicating that this is the specification of choice. to deal with the autocorrelation in equation 17.
Table 4-3. Summary of regression results: OLS estimation.

Dependent variable: \( g_{PI} \) (Average annual growth rate of real Personal Income)
- Mean value: 2.49779
- Standard deviation: 0.875947

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>Probability</th>
<th>Value</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>1.61472</td>
<td>0.00000</td>
<td>1.6011</td>
<td>0.00000</td>
</tr>
<tr>
<td>( g_{services} - g_{manuf} )</td>
<td>-0.08600</td>
<td>0.00442</td>
<td>-0.05285</td>
<td>0.09824</td>
</tr>
<tr>
<td>( e_{services} - e_{manuf} )</td>
<td>0.96948</td>
<td>0.00000</td>
<td>0.97180</td>
<td>0.00000</td>
</tr>
<tr>
<td>( g_{pop} )</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.91901</td>
<td></td>
<td>0.90863</td>
<td></td>
</tr>
<tr>
<td>Adjusted ( R^2 )</td>
<td>0.91541</td>
<td></td>
<td>0.90457</td>
<td></td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-1.42918</td>
<td></td>
<td>-4.3231</td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>8.85837</td>
<td></td>
<td>14.6462</td>
<td></td>
</tr>
<tr>
<td>SC</td>
<td>14.472</td>
<td></td>
<td>20.2598</td>
<td></td>
</tr>
</tbody>
</table>

Regression diagnostics:

<table>
<thead>
<tr>
<th>Multicollinearity Index</th>
<th>5.11499</th>
<th>7.49177</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jarque-Bera</td>
<td>12.51547</td>
<td>10.8705</td>
</tr>
<tr>
<td>Breusch-Pagan</td>
<td>2.448457</td>
<td>2.59820</td>
</tr>
<tr>
<td>Koenker-Bassett</td>
<td>1.263263</td>
<td>1.42171</td>
</tr>
<tr>
<td>White</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Diagnostics for spatial dependence:

| LM (lag)                | 2.415431| 0.120245| 5.94617  | 0.01474   |
| Robust LM (lag)         | 0.112981| 0.736775| 0.87581  | 0.34935   |
| LM (error)              | 13.26660| 0.000270| 18.98270 | 0.00001   |
| Robust LM (error)       | 10.96355| 0.000929| 13.91234 | 0.00019   |

For equation 18, both the spatial lag and spatial error LM statistics are significant. Since of the robust LM statistics only the LM (error) is significant, a spatial error model is the best choice between the two models.

The results of the spatial lag and spatial error models are shown in Table 4-4.
Table 4-4. Summary of regression results: Maximim Likelihood estimation.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>Probability</th>
<th>Value</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable: $g_{PI}$ (Average annual growth rate of real Personal Income)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Spatial Error</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>1.55627</td>
<td>0.00000</td>
<td>1.67658</td>
<td>0.00000</td>
</tr>
<tr>
<td>$g_{services} - g_{manuf}$</td>
<td>-0.06491</td>
<td>0.01207</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$e_{services} - e_{manuf}$</td>
<td></td>
<td></td>
<td>-0.06660</td>
<td>0.00634</td>
</tr>
<tr>
<td>$g_{pop}$</td>
<td>0.96137</td>
<td>0.00000</td>
<td>0.92610</td>
<td>0.00000</td>
</tr>
<tr>
<td>Lambda</td>
<td>0.64786</td>
<td>0.00000</td>
<td>0.73021</td>
<td>0.00000</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>5.71569</td>
<td></td>
<td>6.09924</td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>-5.43138</td>
<td></td>
<td>-6.19849</td>
<td></td>
</tr>
<tr>
<td>SC</td>
<td>0.18222</td>
<td></td>
<td>-0.58489</td>
<td></td>
</tr>
<tr>
<td>Breusch-Pagan</td>
<td>30.278309</td>
<td></td>
<td>2.21159</td>
<td>0.33094</td>
</tr>
<tr>
<td>Wald</td>
<td>30.278309</td>
<td></td>
<td>55.17365</td>
<td></td>
</tr>
<tr>
<td>Likelihood Ratio</td>
<td>14.28975</td>
<td>0.00015</td>
<td>20.8446</td>
<td>0.00000</td>
</tr>
<tr>
<td><strong>Spatial Lag</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$g_{PI}$ lagged</td>
<td>0.16447</td>
<td>0.01410</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.17625</td>
<td>0.00000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$g_{services} - g_{manuf}$</td>
<td>-0.05873</td>
<td>0.03928</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$e_{services} - e_{manuf}$</td>
<td></td>
<td></td>
<td>0.88900</td>
<td>0.03928</td>
</tr>
<tr>
<td>$g_{pop}$</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Likelihood</td>
<td></td>
<td>-1.41997</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td></td>
<td>10.8399</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SC</td>
<td></td>
<td>18.3247</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Breusch-Pagan</td>
<td></td>
<td>1.44063</td>
<td>0.48659</td>
<td></td>
</tr>
<tr>
<td>Wald</td>
<td></td>
<td>6.02507</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Likelihood Ratio</td>
<td></td>
<td>5.80627</td>
<td>0.01596</td>
<td></td>
</tr>
</tbody>
</table>

The statistically significant spatial error coefficient suggests that the autocorrelation may be due to the fact that the data are aggregated on the basis of state boundaries, which have political but no economic meaning. The statistically significant spatial lag coefficient suggests that a state’s economic growth is significantly affected by the growth of its neighboring states. In the spatial error as well as the spatial lag
specifications, the extent to which the services sector expands faster than the manufacturing sector is negatively related to income growth.

For spatial error and spatial lag models, goodness of fit can be measured by an increase in the Log-Likelihood, or decreases in the Akaike Information Criterion (AIC) and Schwartz Criterion (SC). In all 3 cases, the maximum-likelihood estimation improved the fit. Furthermore, as the robust LM (error) statistic suggested, the spatial error model is indeed a better fit than the spatial lag model for Equation 17. The Breusch-Pagan test does not point to a problem with heteroskedasticity, and the Wald test is greater than the Likelihood Ratio test, as expected for finite samples.

4.4.1 Conclusion

The purpose of this study was to investigate whether the recent downturn in the manufacturing sector, and the expansion of the services sector, have negative consequences for economic growth in U.S. states. To do so, Kaldor’s laws of economic growth were examined. These laws embody Kaldor’s theory of cumulative causation for economic growth, with the manufacturing sector as the engine of that growth. Using Personal Income and employment data for the period 1990-1997, the results of a t-test comparing means for independent samples indicate that states with declining manufacturing sectors in terms of employment had significantly lower growth than states with increasing manufacturing sectors. Furthermore, spatial econometric analysis shows evidence that when the services sector expands faster than the manufacturing sector, income growth slows down.

This outcome is consistent with Kaldor’s model of cumulative causation, which argues that regions specializing in manufacturing will be able to reap the benefits of
economies of scale. Specialization in manufacturing will provide the region with labor productivity gains through innovations and technological advances endogenous in a growing manufacturing sector, a process of learning by doing. These productivity gains will increase the region’s competitiveness. Greater competitiveness, in turn, induces greater demand for the region’s production, further expanding the manufacturing sector. This growth feeds back into further productivity gains (Kaldor 1966). Specialization in services does not appear to have this effect.

These are important findings from the perspective of regional economic development. They imply that public policy intended to stimulate regional economic growth should concentrate on strengthening the manufacturing sector. Some of these policies should originate at the federal level. For example, Bivens et al. (2003) suggests that first and foremost, manufacturing needs relief from the ballooning trade deficit. In particular, it will be necessary to remove the artificial cost advantages enjoyed by countries that peg their currency to the dollar by putting pressure on these countries to allow the dollar to depreciate. Furthermore, trade agreements should contain meaningful provisions for enforcing internationally recognized labor and environmental standards. Failure to incorporate such provisions in the latest trade agreements have resulted in further artificial cost-advantages over the U.S. for many countries.

Manufacturing firms also need relief from rising health care costs. Manufacturing firms have traditionally been more likely than firms in other sectors to offer good benefit packages to their employees, which is a policy that should not be discouraged. Many manufacturing firms now face large “legacy costs,” contractual obligations to retirees, exacerbated by recent increases in early retirements. Public initiatives could take the
form of lowering the eligibility age for Medicare for retirees, including prescription drug coverage, or subsidies for firms with large legacy costs (Bivens et al., 2003).

An important public policy initiative in support of manufacturing is the National Institute of Standards and Technology’s Manufacturing Extension Partnership (MEP) program, which helps small and medium-sized manufacturers become more productive and competitive. A network of MEP Extension Centers exist because of a partnership between the federal government, state and local governments, and industry. Drastic cuts in federal spending on this program have been proposed repeatedly in recent years, and have met with strong opposition from Congress and manufacturing organizations alike. The National Association of Manufacturers (NAM) estimates that MEP may be credited with helping to create or save more than 53,000 jobs in 2005 alone, stimulating more than $2.2 billion in economic growth.

Wial and Friedhoff (2006) call for increased funding for MEP, both at the federal and at the state level. They suggest a number of further policy initiatives at the state level. These policies should be geared toward retaining and strengthening a state’s existing manufacturing base, instead of expensive efforts to entice manufacturers from other states to relocate. For example, Pennsylvania funds an early warning system that identifies manufacturing plants at risk of closing and intervenes to help them remain competitive. State policies designed to attract manufacturers from out of state, particularly if they involve providing financial incentives, should always be tied to a mandate that these manufacturers buy a substantial portion of their components and raw materials locally. Strong backward linkages within the region are not only beneficial to local economies, they serve as an incentive for firms to be less “footloose.”
4.5 Works Cited


CHAPTER 5

SUMMARY AND CONCLUSIONS

“A nation without manufacturing is like a car without gas – it will not move forward.” These are the words of Professor Thomas Eagar of M.I.T. in his testimony before Congress (Eagar, 2003). According to Professor Eagar, the only sectors of the economy that generate material wealth are agriculture, mining, manufacturing, and construction. Of these, manufacturing is unique in that it is not limited by natural resources (as are agriculture and mining), and its products can be easily exported (unlike construction). Other sectors, such as services and trade, can only redistribute wealth.

Yet, there is talk of other sectors, such as services and trade, replacing manufacturing in the future. Some even say the future is now. Is manufacturing in crisis? The number of direct labor jobs in manufacturing has been decreasing for several decades. The U.S. has lost its manufacturing position in textiles, shipbuilding, and consumer electronics. The steel industry is a fraction of its former size, and semiconductors are starting to decline. Compounding these challenges, the most recent (2001-2003) recession, which by all accounts was rated as relatively mild, dealt a serious blow to manufacturing. Manufacturing output fell by 6 per cent; manufacturing employment fell by 2.6 million jobs, accounting for all the net job losses during that period; and recovery in manufacturing lagged well behind the rest of the economy. Manufacturing employment still has not returned to its former peak (U.S. Department of Commerce, 2004).
The precipitous loss of manufacturing jobs has brought about an impassioned debate over its causes. The most obvious culprit is globalization – outsourcing and foreign imports, and the recent trade with China in particular. Some see the “inexorable march of technological progress” similar to the industrial revolution of the nineteenth century. Then there is the argument that productivity in the manufacturing sector has increased so much that demand for manufactured goods simply cannot keep pace. Also, there is some evidence that demand may have shifted away from manufactured products toward services, particularly health care and purchased services formerly performed within households. Finally, there may be some statistical artifact at work, in that manufacturers increasingly concentrate on their core competencies, contracting out support services. As a result, jobs previously considered manufacturing are now tallied as services. In addition, there is a tendency among manufacturers to meet short-term fluctuations in demand by hiring temporary workers through agencies, also adding to service sector employment.

Within the context of this debate, this dissertation contains three separate essays, each with a different perspective on the shift in employment trends from manufacturing to services. Each also highlights a different spatial methodology. The first essay, in Chapter 2, contrasts geographic concentrations of manufacturing and service sector employment across U.S. counties, and analyzes the evolution of these clustering patterns over the 1990-2003 study period.

The “most widely used concentration index in the analysis of regional patterns” is the locational Gini coefficient (Stirboeck 2002). Gini coefficients are traditionally used in economics to measure the unequal distribution of a particular variable, particularly income. They are derived from a Lorenz curve, a cumulative frequency curve that is
compared to a uniform distribution representing perfect equality. Similarly, the locational Gini coefficient, developed by Paul Krugman (1991), is derived from a spatial Lorenz curve. It measures the extent of industrial localization and regional specialization, taking into account the relative concentration pattern of a particular sector in one county with respect to the same sector in other counties. As calculated by Kim et al. (2000), the coefficient ranges in value from 0, indicating employment shares for the sector are evenly distributed across counties, to 0.5, indicating all employment for the sector is concentrated in one county.

The locational Gini coefficient is a summary measure. It provides information about the level of concentration (or dispersion) of a particular sector, and can be used to compare that to other sectors. However, it does not provide any further information about the geographical distribution of the counties where the employment in a sector of interest is concentrated. These counties may be spatially concentrated or randomly distributed. Thus, a county that has a strong concentration of, say, manufacturing employment, may or may not be part of a multi-county manufacturing cluster.

To overcome this problem, the Getis-Ord $G^*_i$ statistic is used as a measure of concentration in Chapter 2. It is a multiplicative measure of spatial concentration that distinguishes between clusters of high values and low values of the employment variable under study (i.e., manufacturing or services). The value of $G^*_i$ for each county is based on the value of the employment variable for the county itself as well as that of neighboring counties. In this fashion, the $G^*_i$ detects concentrations across county boundaries.

When no adjustment is made for geographic size or population, significant clustering is evident, and the patterns are similar for both manufacturing and services.
Most clusters show consistent expansion over time. Some were stable, but few declined. Even in the “Rust Belt” the clusters were stable or showed moderate improvement. An interesting observation is made: the clustering of the service sectors predates that of manufacturing. Since the $G^*_t$ statistic measures clustering relative to national average employment levels, it is not possible to fully explain this phenomenon from this measure alone. At first glance, it may seem that manufacturing is drawn to locations with well-established services; on the other hand, in light of the decline in manufacturing employment nationwide, another explanation may be that manufacturing is less likely to leave an area where services are ubiquitous. This will be a topic for future research, as well as the interaction between manufacturing and services.

When clustering is examined for employment data normalized by population, differences in location patterns between manufacturing and services become evident. Manufacturing employment relative to the population tends to cluster, service sector employment relative to the population is more dispersed. Furthermore, the clustering of manufacturing employment relative to the population diminishes over time. This is most likely due to the fact that populations tend to follow manufacturing employment. A strong manufacturing presence in a sparsely populated area tends to draw population to that area; while the same cannot be said for services. Again, this is an area that warrants further investigation.

A growing cluster of both manufacturing and services employment in Northeast Ohio is examined in closer detail for the strength of its industrial linkages. In spite of substantial manufacturing employment losses, manufacturing has remained the economic base for these counties. Five key industries are identified, all in manufacturing.
The second essay (Chapter 3) addresses the ongoing “New Economy” debate. The merits or dangers of an evolution towards a service economy are examined. In most studies, national data are used to show the long-run shift away from manufacturing employment, ignoring regional variations. In order to better inform this argument, Chapter 3 concentrates on the Great Lakes states, where manufacturing job losses have been particularly severe. To aid the analysis of job loss patterns over space and time, this essay demonstrates the use of a geostatistical technique called kriging. Kriging smoothes the spatial distribution of the variable under study, which greatly enhances its visualization. A widening of the color bands and a general deepening of the color ramps in the kriged map show a gain in manufacturing jobs prior to 1997, particularly in Indiana, Michigan, and Wisconsin. Between 1997 and 2003, however, manufacturing employment declined across the entire region, down to levels below those of 1990.

In addition to its ability to augment the visual inspection of patterns of spatial variation, kriging provides a powerful stochastic interpolation methodology to estimate missing values. The public use data drawn on for this dissertation contains a number of missing data points. In most cases, information was withheld because of confidentiality concerns. While other, deterministic interpolation methods could have been used to estimate the missing values, a stochastic methodology such as kriging has the advantage that it allows for the application of standard statistical inference procedures to assess the validity of the interpolation results.

The first and second essays are exploratory examinations of employment patterns; their purpose is not to answer a particular research question. However, the third essay (Chapter 4) is an empirical study. It investigates the theoretical underpinnings for the notion that the manufacturing sector is responsible for the
increases in our standard of living. In particular, this essay reviews Kaldor’s three laws – empirical relationships that together embody his theory of cumulative causation for economic growth, with the manufacturing sector as the engine driving that growth. Nicholas Kaldor was a Cambridge economist whose work on endogenous technical progress, resulting in increasing returns to scale, predates by 30 years the similar modern endogenous growth theories. Rather than estimate Kaldor’s laws, as most other studies on Kaldor’s laws have done, Chapter 4 tries to determine if manufacturing is a better engine of economic growth than services. The econometric model incorporates the spatial autocorrelation and heterogeneity that were found in Chapters 2 and 3. Failure to do so would constitute a specification error.

From the preliminary analysis of the data it is apparent that the 2000-2003 recession had a disproportionate effect on the manufacturing sector. Whereas total Personal Income only leveled off and then started to rise again, earnings from manufacturing declined sharply, and have not yet recovered. Furthermore, manufacturing employment as a share of total employment in the U.S. declined steadily during the entire study period, while services employment shares rose.

The results of Chapter 4 indicate that there is a significant difference in the Personal Income growth rates of states where manufacturing employment is growing and states where manufacturing income is falling. Furthermore, when the services sector grows faster than the manufacturing sector, either in terms of income or in terms of employment, it has a deleterious effect on income growth for that state.

Future research is planned to study similar effects using data at the county level or finer.
5.1 Works Cited


