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Does Manufacturing Still Matter?

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Abstract Although employment in the manufacturing sector has declined over the past few decades, it continues to play an important role in many regions of the U.S. Most studies have not examined the spatial effects of manufacturing employment on regional job quality. In this paper, we consider the spatial dependence and spatial variation of this relationship in the Midwest. This analysis suggests that it is important to take into consideration spatial effects when examining the implications of economic restructuring for regions. Labor market areas are not distinct spatial units and can be influenced significantly by nearby local labor markets. Once that spatial dependence is considered, manufacturing has a negative and significant effect on underemployment by low earnings, but its effect is not significant in labor hardship associated with work time and steadiness. At the same time, our analysis demonstrates that the effects of manufacturing employment vary across local labor markets. More specifically, these findings suggest that in those areas in the Midwest that have historically had higher concentrations of manufacturing jobs, the benefits of working in this sector are smaller. In regions that have not had a large manufacturing sector and have experienced some gains in recent years, the benefits of working in the manufacturing sector are larger.

Keywords Manufacturing · Spatial effects · Spatial distribution · Underemployment

The manufacturing sector has historically provided middle-class jobs that offered a path for upward mobility to workers. Manufacturing employment also has constituted the base for many regional and local economies, thanks to its multiplier effects on

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other sectors and its influence on labor market standards. Baker and Lee (1993) estimate that the average manufacturing job generates 4.2 additional jobs in the economy. It has even been suggested that the strong manufacturing sector has been the pivotal feature of wealth and power of the United States (Cohen and Zysman 1987).

This paper addresses the latter issue by examining the extent to which manufacturing matters for county underemployment levels in the Midwest. There continues to be much debate over the significance of the manufacturing sector in today's economy (Ramaswamy and Rowthorn 2000). Although the loss of manufacturing jobs has been well documented, few analyses have paid attention to spatial aspects of the relationship between manufacturing and job quality. Such assessment is necessary to explore questions pertaining to differences in underemployment levels across space, the geographical distribution of manufacturing employment, and its effects within and beyond county boundaries.

This issue has some obvious substantive and policy implications. First, many communities continue to attempt to attract manufacturing firms because local officials believe that manufacturing jobs continue to be the base of regional economies. If the manufacturing sector no longer supplies better jobs or has the same multiplier effect, then we may need to rethink local economic development strategies. Second, it may be the case that the manufacturing sector has different effects in different regions. Thus, policy makers may have an interest in understanding where manufacturing jobs are likely to have the greatest payoff.

Substantively this paper considers three issues: (1) the spatial distribution of underemployment using four distinct measures; (2) the effect of manufacturing on underemployment taking into account spatial dependency among counties; and (3) the variation in the effects of manufacturing across space. To look at these issues we combine insights from Exploratory Spatial Data Analysis (ESDA), spatial econometrics, and Geographically Weighted Regression (GWR).

In the following section we briefly review existing research and discuss industrial trends that may have transformed the effect of manufacturing on job quality. Next, we present trends on manufacturing employment in the Midwest and make the case for spatial analysis. The third section describes the data and methods, and the fourth section presents the results. Finally, we discuss our findings and future lines of research.

The Changing Manufacturing Sector and Underemployment

Previous research on underemployment has examined the effect of manufacturing on individual employment opportunities (Elliott 2004; Jensen et al. 1999; Lichter 1988). This research suggested that during the 1970s and 1980s manufacturing employment positively influenced earnings, job stability, and standard work hours. Furthermore, studies pointed to the negative effects that deindustrialization had on residents of traditional manufacturing sites, especially for minority workers (Wilson 1996; Bound and Holzer 1993).

The manufacturing sector has a direct effect on local employment levels, earnings, and income distributions (Lobao et al. 1999; Friedman and Lichter 1998;

Lorence and Nelson 1993; Bloomquist and Summers 1982). Research also suggested an indirect impact through multiplier effects by producing jobs in other sectors and higher income levels (Shaffer et al. 2004). Places with high levels of manufacturing employment had higher earnings and lower levels of income inequality (Lobao 1990). Analyses of 1990 data suggested that manufacturing employment had a positive effect on median income family and in reducing local inequality (Lobao et al. 1999). Interestingly, Lobao et al. (1999) reported that both core-manufacturing and peripheral-manufacturing employment increased family income in 1970 and 1990. This finding supports Bluestone and Harrison's (1982) claim about the beneficial impacts of manufacturing, not only due to its higher wages and better benefits, but also to its degree of embeddedness in local contexts.

Several factors have contributed to the deindustrialization process, such as globalization, technological change, and the decline in unionization. These changes are most evident in the Midwest, where the manufacturing based has contracted the most in the last few decades. Low-wage, low-skilled manufacturing firms have shifted much of their production to lower cost areas. Technological change, especially computerization, has increased worker productivity skills, ultimately decreasing the demand for workers with low levels of skills. The decline of union power has permitted corporations to rely more on outsourcing and use of temporary workers.

Economic restructuring has influenced not only the size of the manufacturing sector, but it also may have changed the character of jobs that remain. Globalization may reduce the number of manufacturing jobs, but those that remain may be high-wage, high-skilled jobs that are not exposed to the same level of foreign competition. Job losses through globalization tend to be restricted to the low-skilled positions. Thus, while the restructuring process ultimately reduces the size of the manufacturing sector, the remaining jobs may provide higher wages and offer more benefits than in the past.

Technological change may have similar effects. Although technological change reduces the number of manufacturing jobs, those that remain may be of higher quality. Technological advances increase the demand for higher skilled workers and reduce low-skilled jobs.

Declining union power may run counter to these trends. With less bargaining power, the manufacturing sector may have fewer benefits and less job security. Also, union presence has been found to be strongly related to training upgrading by employers in some studies (Knoke and Kalleberg 1994). Other associated changes may also affect the quality of jobs in the manufacturing sector. For example, adoption of flexible manufacturing practices may have led to the growth of part-time and temporary workers (Tilly 1996).

Manufacturing often provides the economic base of a locality and creates additional jobs through the purchase of local goods and services. Export base theory posits that the export sector is the proportion of a locality's goods and services that is traded with other regions (Shaffer et al. 2004). The export sector creates the demand for goods and services in the local economy, what is referred to as the nonexport or nonbasic sector. All things being equal, a larger manufacturing sector should have a greater multiplier effect in the local economy and create more jobs and income, and ultimately more demand for services. Export base theory suggests that as the export base declines, the nonbasic sector should also contract. This argument, however, rests on the assumption that the nonbasic sector is primarily passive and largely dependent on the basic sector. Nonbasic industries, however, often can generate growth and become relatively independent of the basic sector over time. An example could be the retail sector of a locality that becomes large enough to sustain itself. Thus, the decline in the relative share of employment in manufacturing may not have much of an influence on the overall level of employment or income growth in a region, especially if the nonbasic sector is substantially large or is able to draw consumers from a broader region.

Overall, the economic restructuring process raises important questions about the benefits of manufacturing employment for workers and localities. More specifically, the restructuring process may significantly reduce the impacts of the manufacturing sector on the overall health of local economies.

Trends in Manufacturing Employment in the Midwest

In Table 1 we report change in manufacturing employment in 12 Midwestern states from 1977 to 2001. Overall, manufacturing employment declined by more than 22% in the region during this period. This loss would have been much higher if we had included the recession period of 2001 to 2003. Although it is important to consider the overall trend in the region, it is useful to examine the different experiences across the Midwest. States with the largest losses in manufacturing employment were Illinois, Ohio, and Michigan. Several states, however, experienced gains in manufacturing employment. Kansas, Minnesota, and the Dakotas had moderate gains in manufacturing employment during the recession.

The recession of 2001–2003 hit the manufacturing sector especially hard. For example, Wisconsin lost about 12% (59,148 jobs) of its manufacturing employment from the first quarter of 2001 to the fourth quarter of 2003. Illinois lost 21% (194,877 jobs) of its jobs in this sector. Missouri was in between these two extremes, with a loss of 17% (63,111 jobs). The durable goods manufacturing sector lost fewer jobs during the recession than the nondurable goods sector. The manufacturing sector has rebounded a bit, but not to pre-recession levels. It is unclear what these compositional changes mean for localities. Although the skill level and wages may rise in the manufacturing sector, the overall income in localities may fall if service sector jobs do not provide higher wages.

These patterns of industrial change differ across metropolitan and nonmetropolitan areas. During much of the 1990s, nonmetropolitan areas experienced a larger decline in low-skilled work than did metropolitan areas. The largest declines tended to be in the apparel industry, and the yard, thread, and fabric mill industry (Gibbs et al. 2004). The net result of these changes and technological advances has been that the share of low-skilled jobs has declined since 1990. Although service sector jobs overall paid less than jobs in the goods sector, part of the decline in low-skilled jobs in nonmetropolitan areas can be attributed to higher-skilled jobs being created in the service sector (Gibbs et al. 2004). The likelihood that service sector jobs will

Table 1 Manufacturing employment in the Midwest, 1977–2001

	Illinois	Indiana	Iowa	Kansas	Michigan	Minnesota	Missouri	Nebraska	North Dakota	Ohio	South Dakota	Wisconsin	Midwest
All employees. Thousands													
1977	1286.2	705.9	240.3	168.1	1115.9	331.7	433.3	98.8	13.8	1331.2	22.5	535.0	6282.7
1982	1077.4	585.1	213.3	170.6	883.9	351.6	406.0	91.7	14.8	1108.4	24.5	496.8	5424.1
1987	989.6	602.0	206.1	189.1	980.1	374.2	418.8	90.7	15.4	1100.2	27.5	514.0	5507.7
1992	968.0	620.3	227.3	188.1	916.5	391.6	408.8	100.1	18.4	1044.2	35.2	546.0	5464.5
1993	978.5	625.3	235.2	184.7	917.0	398.8	410.9	101.1	19.4	1049.9	37.0	551.2	5509.0
1994	989.6	647.6	249.0	198.2	936.5	409.7	401.7	107.6	20.7	1045.5	38.9	576.9	5621.9
1995	1006.1	672.7	254.1	203.6	971.5	419.1	411.8	110.4	21.9	1038.1	41.5	598.6	5749.4
1996	996.3	660.0	250.4	209.2	966.5	432.2	414.9	110.1	22.1	1073.5	45.6	601.0	5781.8
1997	883.4	625.7	236.9	193.0	828.4	379.9	367.5	106.6	21.9	980.1	46.3	560.6	5230.4
1998	891.5	627.3	249.2	201.5	830.8	388.1	362.1	111.4	22.7	993.3	47.2	569.6	5294.7
1999	873.6	633.7	242.4	198.7	815.0	386.0	366.0	110.4	22.6	980.1	48.4	571.0	5247.9
2000	865.7	638.2	246.8	195.7	807.7	390.3	360.9	110.4	24.0	982.2	41.8	572.2	5235.9
2001	811.3	597.7	235.9	193.8	749.5	376.7	346.6	105.0	23.4	923.5	39.6	544.3	4947.3

Source: Annual survey of manufacturers. Geographical area statistics 1994, 1996, and 2001 pay higher wages on average than low-wage manufacturing jobs is much greater in metropolitan than nonmetropolitan areas (Goe 2002).

Spatial Dimension of Labor Markets

It is well documented that labor markets vary in terms of their scale of operation (local, regional, or national) and their structure (occupational/industrial or gender/racial composition) (Jenkins 2004; Beggs and Villemez 2001; Martin 1998). Several studies also have documented variation in unemployment rates, income inequality, median earnings, and underemployment across regions and counties (Lobao 2004; McCall 1998). Although documenting variations in the dependent variable is in itself important to characterize distinctive employment opportunities structures, it does not fully consider the spatial dimension of labor markets. Greater attention needs to be paid to the effect that neighboring economies may have on local labor markets (spatial autocorrelation between counties) and to variations in the association between labor hardship and explanatory factors (a nonstationary relationship).

There are both substantive and methodological reasons for considering the spatial effects of industry on well-being. As Martin (1998) claims, regional or local disparities have to inform labor market theories and policies since these scales mediate national and international processes in terms of their local economic structures, labor force supply, and institutional forms. The literature on labor markets and industrial restructuring has long acknowledged that labor standards (e.g., wage levels, hiring conditions, or job stability) at one location influence conditions in neighboring labor markets (Beggs and Villemez 2001; Martin 1998; Sassen 1995). Such effects are likely to emerge because employers are competing for workers residing in nearby locations. Competition can lead employers to improve labor conditions as recruitment strategy or to pursue new supplies of labor force (Clark et al. 1986; Martin 1998). Unions could also play a role by demanding labor standards similar to those in nearby locations.

Manufacturing industries also tend to cluster in certain areas, and that industrial reorganization tends to be imitated by industries sharing a common area. In our study, it is possible to assume that county job quality is likely to be influenced by prevailing standards in the surrounding labor markets. Manufacturing could affect underemployment levels not only in the locality but also in neighboring counties because its labor supply may be located across different counties. More importantly, manufacturing may have indirect effects by shaping wage levels and hiring conditions in other sectors and counties.

Considering the potential effects that adjacent or nearby counties could have on job quality indicators requires techniques that handle spatial dependence across units. Spatial dependence refers to value association between observations that are geographically near to each other. Positive autocorrelation is present when units that are geographically closer tend to have similar values, that is, a tendency to form clusters: counties with low underemployment will tend to be located nearby other low county values, while high values will tend to be surrounding by high underemployment places. This spatial pattern may suggest common processes across counties that lead to similar levels of underemployment, above and beyond counties' structural characteristics.

Ignoring spatial dependency could affect the reliability of findings by either overestimating the significance of the results or by producing biased estimates, depending on the spatial process at place. Spatial dependency in the error terms is a sign of model miss-specification (e.g., omitted variables that are themselves spatially autocorrelated). This type of spatial dependence violates the OLS assumption of uncorrelated errors. When this type of spatial dependency is ignored the OLS will be inefficient; the *t* and *F* statistics will be biased and the R-Squared deceptive (Anselin 1992a). Spatial econometrics techniques allow specifying a model that considers this dependency in the errors: the spatial error model.

Substantive spatial dependency is present when the value of an observed variable at each place actually determines the value at nearby locations (Baller et al. 2001; Anselin 1992a). Ignoring substantive spatial dependency will yield biased estimates. A spatial lag model specifies this type of spatial association by introducing a lag variable, which assesses the degree of spatial dependence. Following Baller et al. (2001) it is possible to conceptualize a spatial lag model as one that considers interactive relationships between dependent and independent variables at neighboring units. In other words, the spatial lag model accounts structural similarities across counties (e.g., explanatory variables) and for similarities in their underemployment levels beyond each county composition. This model suggests a process of contagion across units, in such a way that job quality indicators respond to employment conditions in the surrounding locations and not only to county determinants.

Thus, the presence of spatial autocorrelation needs to be considered since it could inform the substantive process at a place suggesting reciprocal influences in setting labor standards or employment patterns, as well as because it generates estimation problems that could lead to erroneous conclusions.

Another issue to consider is the extent to which manufacturing has the same effect on job quality across space. According to the literature we would expect a nonstationary relationship since spatial variation could reflect place differences in industrial trajectories, diverse degrees of interconnection between manufacturing and local economies, or even diverging "routes" of economic restructuring.

Data and Methods

Data for this analysis are drawn from the 2000 Census of Population and Housing (summary file 4). We use county-level data from twelve Midwest states: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin. The total number of counties is 1056. Our dependent variables include four dimensions of underemployment identified in the literature: low hours, low income, part-time employment and intermittent employment. Low hours underemployment is defined as usually working fewer than 35 hours a week, regardless of how many weeks are worked. Low income is defined as earning at or below 1.15 ratio of income to individual poverty level. Part-time employment is measured as working fewer than 35 hours per week for 50 or more weeks during the year. Intermittent employment is defined as working between 15 and 49 weeks during the year.

Together, these variables evaluate employment quality based on work time (hours), steadiness (as measured by the number of weeks employed), and earnings. However, given the limitations of census data, it is not possible to fully distinguish among those who experience labor hardship and those who choose to work under those conditions. For example, it is not possible to distinguish between those working part-time because they decided to do so and those working part-time because they could not find another job. However, the census is the only source to provide sound estimates at the county level for all the variables in this analysis.

We focus primarily on the effect of manufacturing on underemployment measures. We include as control variables whether a county is in a metropolitan area or not, the percentage of service employment, the percentage of labor force with less than high school education, and the percentage of population with college education and up. In addition, female labor force participation and the percentage of foreign-born population, black, and other race population are also included as controls. As an indicator of prevailing family structures we include a variable measuring the proportion of female-headed families.

Based on the previous literature on underemployment, these independent variables should be correlated with several of the dimensions of underemployment. Human capital theory suggests that education levels should be positively related with the percentage of low-wage workers in the labor market. Lichter (1988, 1989) has found race to be strongly correlated with underemployment; blacks have much higher rates of underemployment. Regions with a high proportion of female-headed households also should have higher rates of underemployment (McCall 1998). Finally, higher rates of female labor force participation should be negatively related to underemployment rates (Browne 1997).

Several independent variables had a skewed distribution so we transformed these variables by using the natural logarithm. The following variables were transformed: the percentages of female-headed families, foreign-born population, black population, and other race (nonwhite) population.

On average across counties, one-fourth of the workers in the region are considered underemployed by low hours. Ten percent are part-time employees. About 26% are intermittent workers and about the same percentage are underemployed by low income. Although the primary focus of this paper is on the effects of manufacturing employment, it should be recognized that the vast majority of jobs in most labor markets are in the service sector. The average county in the Midwest has only about 17% of its employment in the manufacturing sector and 48% in services. Approximately 18% of the average county's population had less than a high school degree. About 16% had a college education or more. A relatively small proportion of the population in the average county was foreign-born. Female-headed households constituted 11% of families.

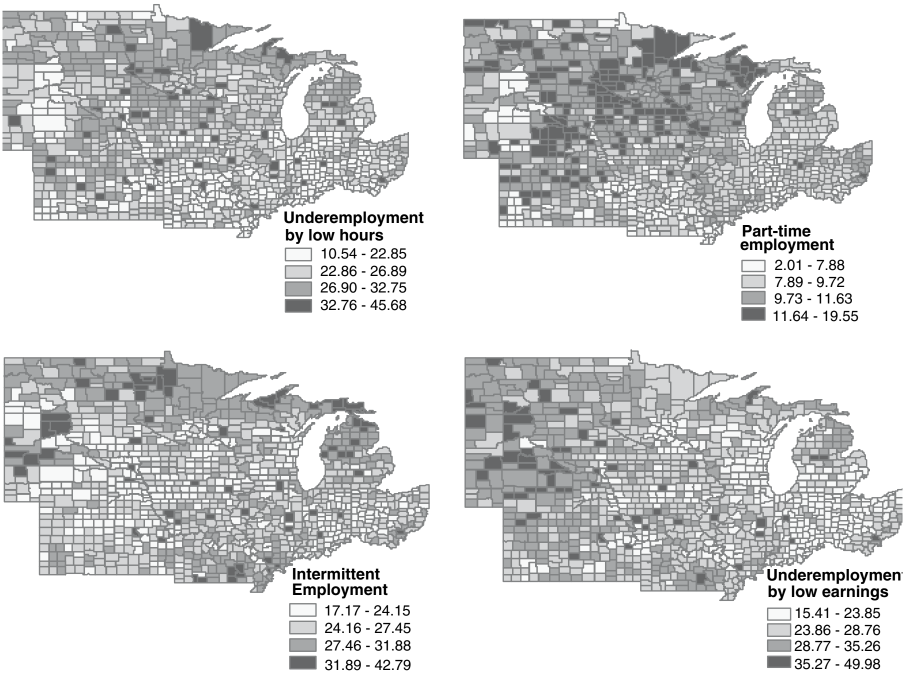

Fig. 1 The geographic distribution of underemployment

Results

As can be seen by the maps of these four dimensions of underemployment, the measures of underemployment exhibit clear spatial patterns (Fig. 1). The highest levels of low hours tend to be concentrated in northern Michigan, the Upper Peninsula of Michigan, and northern Minnesota. This area tends to rely heavily on tourism as its economic base. Low income workers tend to be concentrated in the Ozark region of southern Missouri and in the Dakotas. Part-time employment is concentrated in the Upper Peninsula of Michigan, much of rural Minnesota, and northeastern Nebraska.

To measure spatial association between county underemployment we first compute univariate Moran's I, which measures the association among underemployment values in nearby locations. A positive value suggests a spatial cluster of similar values. That is, counties with high values in the dependent variable tend to be surrounded by high values while low values are surrounded by other low value observations. We use a queen-based contiguity weight matrix to calculate the Moran's I, which defines as neighbors adjacent counties that have common points (boundaries or vertices). This weight matrix corresponds to a geographically limited area within which workers may be more likely to commute. In our data set a queen matrix yields a weight structure in which all counties have at least one neighborhood (no islands). Three counties have only one neighbor and one has eleven neighbors. The mode is 6 neighbors (with 389 counties falling within this category).

Table 2 Moran's I test for spatial autocorrelation

	I value	Mean	St.Dev	Z-value	Prob
Underemployment by low hours	0.2945	–0.0010	0.0184	16.0596	0.0000
Part-time employment	0.4884	–0.0010	0.0184	26.5995	0.0000
Intermittent employment	0.3254	–0.0010	0.0184	17.7397	0.0000
Full-time employment	0.3562	–0.0010	0.0184	19.4139	0.0000
Underemployment by low income	0.4638	–0.0010	0.0184	25.2611	0.0000

As Table 2 shows, the four underemployment measures exhibit a positive and significant spatial association. The Moran's I measures, however, provide only a limited view to spatial associations between county underemployment percentages because the observed clustering of similar values could be reflecting the spatial distribution of explanatory factors. For example, positive autocorrelation of part-time employment observed in the given area could be expressing similar levels of manufacturing employment or female labor force participation in those counties. Spatial models consider the presence of spatial autocorrelation after controlling for county characteristics.

Spatial Regressions Models

For each of our dependent variables we first estimate Ordinary Least Squared Regression with spatial diagnostic tests using SpaceStat software. Spatial autocorrelation is significantly present in all of the dependent variables, strongly supporting the need for implementing spatial regression models. In a first trial, spatial heteroscedasticity was also present (results not shown). This is a common issue when pooling data from units that are considerably different in size (Anselin 1992b). We introduced county population size as a heteroscedastic variable, which made the diagnostic tests for heteroscedasticity no longer significant.[1]

The OLS regressions suggest that manufacturing employment is positively correlated with underemployment by low hours, part-time and intermittent employment, but has a negative effect on low income. All models exhibit positive spatial autocorrelation, therefore such coefficients may be misleading. Thus, we develop spatial regression models to account for spatial autocorrelation. Here, we report only the outcomes for the spatial model favored by such diagnostic tests (spatial lag model or spatial error model). Tables 3, 4, 5, 6 present OLS and spatial model outputs.

For low hours, the diagnostic test favored an error model specification. The manufacturing coefficient becomes negative, though not significant in the error model (Table 3). The latter model also suggests that metropolitan status significantly decreases the proportion of those underemployed by low hours, as

[1] Implemented in SpaceStat, we introduce population size as a heteroscedasticity variable. The transformation computed is $\sigma^2 = \sigma^2 f\,(\alpha_0 + \Sigma_p Z_{pi}\ \alpha p)$.

Table 3 Underemployment by low hours

Underemployment by low hours	OLS model	Spatial error model
Constant	26.367***	25.072***
Metro	–2.274***	–1.331***
% Manufacturing employment	0.057**	–0.021
% Services employment	0.277***	0.210***
% <High school education	–0.093**	0.012
% College(+) education	0.152***	0.257***
% Female-headed families	–3.906***	–2.516***
% Foreign-born population	0.073	0.279
% Female labor force participation	–0.110***	–0.132***
% Other race population	–0.059	–0.412*
% Black population	0.003	0.079
Spatial variables		
Lamda	–	0.592***
Goodness of fit		
R^2-adjusted	0.3203	0.4763
Log-likelihood	–2796.68	–2699.25
AIC	5615.36	5420.51
SC	5669.93	5475.08
Heteroscedasticity		
Breush-Pagan/Koenker-Bassett Test	Not significant	Not significant
Spatial dependence		
Moran's I (error)	14.4248***	–
Robust LM error	34.2899***	–
Robust LM lag	1.5015	–
Likelihood ratio test	–	194.846***

do female-headed families, female labor force participation and other race population. In contrast, service employment and college educated labor force have a negative, significant effect on low hours. Lambda, an autoregressive parameter measuring spatial dependence in the errors, is positive. It is important to keep in mind the aggregated nature of these variables and the fact that we are predicting a county-level phenomenon that may explain why some variables behave differently than has been found by studies performed at the individual level. For example, individuals with college education may be less likely to experience underemployment by low hours; however, at the county level, an increase in the percentage of college educated actually decreased it. This may be the case, for example, if an educated labor force increases the demand for services that tend to hire workers for non-full time jobs such as those in the food industry or entertainment activities.

In the OLS regression the levels of part-time employment are not significantly related to manufacturing employment (Table 4). The diagnostic test favored a spatial lag model, where manufacturing remains nonsignificant and positive.

Table 4 Part-time employment

Part-time employment	OLS model	Spatial lag model
Constant	11.548***	5.328***
Metro	–0.662***	–0.227*
% Manufacturing employment	0.005	0.007
% Services employment	0.070***	0.046***
% <High school education	–0.053***	–0.017
% College(+) education	–0.013	0.022
% Female-headed families	–2.262***	–1.436***
% Foreign-born population	–0.011	–0.050
% Female labor force participation	0.025	–0.007
% Other race population	–0.146*	–0.214***
% Black population	–0.043	–0.011
Spatial variables		
Lag_variable	–	0.602***
Goodness of fit		
R^2-adjusted	0.2776	0.5085
Log-likelihood	–1988.46	–1827.15
AIC	3998.92	3678.3
SC	4053.49	3737.83
Heteroscedasticity		
Breush-Pagan/Koenker-Bassett Test	Not significant	Not significant
Spatial Dependence		
Moran's I (error)	19.32***	–
Robust LM error	1.57	–
Robust LM lag	66.58***	–

Metropolitan status significantly reduces the levels of part-time employment, as in the case of female-headed households and other race population. Services employment increases part-time employment as expected. The lag variable representing spatial dependence in part-time employment is positive and significant, which suggests that county level of labor hardship is influenced by incidence in nearby locations. Thus, part-time employment exhibits spatial contagion in such a way that similarities across counties respond not only to analogous levels in their explanatory variables, but to employment arrangements in neighboring locations. However, manufacturing employment is not a significant determinant of this pattern.

Intermittent employment exhibits a spatial patterning that is slightly better represented by a spatial error model (Table 5). In this model, manufacturing is associated with an increment in intermittent employment, but its effect is nonsignificant. As in the previous cases, metropolitan status significantly decreases labor hardship, as it does female labor force participation rates. Higher levels of service employment, population with less than high school education, college

Table 5 Intermittent employment

Intermittent employment	OLS model	Spatial error model
Constant	22.940***	22.169***
Metro	–1.920***	–1.611***
% Manufacturing employment	0.047***	0.011
% Services employment	0.239***	0.204***
% <High school education	0.095***	0.133***
% College(+) education	0.050*	0.103***
% Female-headed families	0.119	0.092
% Foreign-born population	0.222	0.196
% Female labor force participation	–0.198***	–0.171***
% Other race population	0.689***	0.526***
% Black population	0.058	0.087
Spatial variables		
Lambda	–	0.480***
Goodness of fit		
R^2-adjusted	0.4139	0.5034
Log-likelihood	–2515.25	–2452.76
AIC	5052.5	4927.52
SC	5107.08	4982.09
Heteroscedasticity		
Breush-Pagan/Koenker-Bassett Test	Not significant	Not significant
Spatial Dependence		
Moran's I (error)	12.40***	
Robust LM error	19.58***	
Robust LM lag	9.51*	
Likelihood ratio test		124.97***

educated population and other race residents tend to increase county levels of intermittent employment. The error variable, lambda, is also significant and positively associated with poor job quality incidence.

Low earnings are clearly better expressed by a spatial lag model, as suggested by the diagnostic tests and the goodness of fit measures. Manufacturing has a highly significant negative effect on county levels of working poor. In this model we also control for part-time employment so that low earnings are not a function of worked hours. As expected, part-time employment is significantly and positively associated with low earnings, as are the percentage of less than high school education, college educated and other race population. In contrast, metropolitan status, foreign-born population, and female labor force participation significantly lessen the prevalence of working poor. As in the case of part-time employment, low earnings is influenced by surrounding county levels, suggesting a process that influences wage levels across units above and beyond each county's structural characteristics. Under the lag model, manufacturing does contribute to reduced underemployment by low

Table 6 Underemployment by low earnings

Underemployment by low earnings	OLS model	Spatial lag model
Constant	35.16***	24.967***
Metro	–3.412***	–2.878***
% Manufacturing employment	–0.213***	–0.155***
% Services employment	–0.044	–0.020
% <High school education	0.080*	0.079*
% College(+) education	0.160***	0.170***
% Female-headed families	1.103*	1.058*
% Foreign-born population	–0.593**	–0.419**
% Female labor force participation	–0.239***	–0.219***
% Other race population	0.684***	0.552***
% Black population	–0.100	–0.0425
% Part-time employment	0.581***	0.526***
Spatial variables		
Lag variable	–	0.275***
Goodness of fit		
R^2-adjusted	0.5363	0.5658
Log-likelihood	–2801.52	–2775.61
AIC	5627.04	5577.22
SC	5686.57	5641.71
Heteroscedasticity		
Breush-Pagan/Koenker-Bassett Test	Not significant	Not significant
Spatial Dependence		
Moran's I (error)	6.824***	–
Ro bust LM error	1.019	–
Robust LM lag	13.79***	–

earnings and its effects extend beyond county boundaries: high percentages of manufacturing decrease low-earnings underemployment at county *i*, which in turn determines labor hardship in the nearby locations, "multiplying" the effect of manufacturing.

The Uneven Effects of Manufacturing Employment Across Place

The second question analyzed in this paper pertains to variations in the relationship between underemployment levels and manufacturing employment across space. We explore this issue through Geographically Weighted Regression (GWR), which allows estimation of local parameters rather than only global ones. A local estimation is computed by using information from units within a bandwidth distance, where closer units have a greater weight than counties farther away. GWR estimates a continuous surface of parameters (Fotheringham et al. 2001, p. 52). GWR examines the implicit assumption of OLS regression that a model applies equally to all regions in the Midwest, when in fact there might be important spatial variation both in terms of the model as a whole and in the specific relationship between the dependent variable and an explanatory variable (Fotheringham et al. 2001). Our models could better fit certain areas in the Midwest than others and manufacturing could matter more in particular regions. That is precisely the pattern we may expect if, as theories suggest, the effect of manufacturing depends on industrial local trajectories and its degree of embeddedness in local economies.

The global regressions computed by GWR are the same as the OLS results presented in Tables 3 through 6. Therefore, in this section we only present the estimates of local parameters for each of our models (Table 7). The GWR analysis suggests that the association between underemployment and manufacturing varies significantly across counties and that our models perform better in certain areas than others. For all models, the local models improve model fits both in terms of an increase in the coefficient of determination and a reduction on the Akaike Information Criterion (AIC) number. The coefficient of determination is computed from a comparison of the predicted values from the model at each point and the actual observed values (Charlton et al. 2003). Larger coefficients of determinations for GWR estimations may be the result of differences in the degrees of freedom, but that is not the case in the AIC, which considers the number of estimated parameters. Thus, models estimating local parameters perform better than global ones.

Figures 2–5 graphically illustrate such patterns. Table 7 presents a summary of local parameters, as well as their significance based on Monte Carlo simulation tests implemented by GWR. In the global regression, manufacturing is positively related to low hours. Local estimates, however, present a more complex picture. Although the association is positive in most areas, its magnitude varies significantly and the relationship is negative in the Upper Midwest. This coincides with patterns suggested by the error spatial regression, where the association between the two variables was nonsignificant. The Monte Carlo simulation test for stationary was barely significant in the case of manufacturing, but it still suggests that manufacturing does not matter equally across the Midwest. Other variables also exhibit a nonstationary relationship with low hours, namely, metropolitan status, service employment, education variables, female labor participation, foreign-born and other race population. Figure 2 shows pseudo local R-squared, which gives a sense of how well the model "replicates the observed values [of our dependent variable] in the vicinity of the point for which the model was calibrated" (Fortheringham et al. 2001, p. 125). The map suggests that the model fits better in Michigan and Iowa than the rest of the region.

The effect of manufacturing in part-time employment (Table 7, Fig. 3) is fairly small and it displays an even greater significant degree of local variability; in fact, the median local estimate is –0.005 while the global parameter estimate is 0.004. In areas where the coefficient is larger (either negative or positive) the parameter are significant, as showed by the *t*-values map. There is also significant variability in the effects of metropolitan status, service employment, and educational variables. Local

Table 7 GWR local regression parameters

	Minimum	Lower quartile	Median	Upper quartile	Maximum	*P*-value Monte Carlo test
Underemployment by low hours						
Metro	7.0516	2.8333	1.7975	1.1322	0.8704	0.0000
% Manufacturing employment	–0.1118	0.0115	0.0633	0.0970	0.2291	0.0500
% Services employment	0.0670	0.1899	0.2659	0.3798	0.7572	0.0200
% <High school education	–0.2976	–0.1019	–0.0185	0.0896	0.4613	0.0000
% College(+) education	–0.1237	–0.0177	0.1537	0.3375	0.6798	0.0000
% Female-headed families	–6.1836	–3.6797	–2.7112	–1.7339	–0.0762	0.0700
% Foreign-born population	–1.8843	–0.4897	–0.1774	0.2977	1.3053	0.0100
% Female labor force participation	–0.3794	–0.1802	–0.1221	–0.0669	0.1617	0.2000
% Other race population	–1.0757	–0.6020	–0.2383	0.2199	1.8704	0.0000
% Black population	–0.3258	–0.0847	0.0102	0.1059	0.5595	0.4900
Part-time employment						
Metro	–2.3467	–0.9429	–0.2956	0.0878	1.1393	0.0000
% Manufacturing employment	–0.1241	–0.0428	–0.0054	0.0257	0.1749	0.0000
% Services employment	–0.1171	–0.0038	0.0341	0.0632	0.3456	0.0200
% <High school education	–0.3333	–0.0685	–0.0244	0.0516	0.2383	0.0000
% College(+) education	–0.2218	–0.0337	0.0042	0.0637	0.2083	0.0100
% Female-headed families	–3.1253	–1.6789	–1.0658	–0.2934	0.7339	0.5700
% Foreign-born population	–1.0293	–0.3192	–0.1103	0.0922	0.7369	0.1100
% Female labor force participation	–0.1194	–0.0421	–0.0118	0.0191	0.1582	0.2600
% Other race population	–0.8694	–0.4299	–0.2825	–0.1187	0.3335	0.6000
% Black population	–0.4189	–0.0916	–0.0179	0.0628	0.2145	0.4000
Intermittent employment						
Metro	–4.2501	–2.1244	–1.6206	–1.2514	–0.7718	0.0800
% Manufacturing employment	–0.0994	–0.0301	0.0185	0.0714	0.2191	0.0000
% Services employment	0.0593	0.1896	0.2350	0.2956	0.4710	0.1200
% <High school education	–0.1190	0.0511	0.1066	0.1834	0.3835	0.0000
% College(+) education	–0.1811	–0.0104	0.0800	0.1599	0.3956	0.0100
% Female-headed families	–2.8752	–0.9367	0.0457	0.6295	1.8366	0.4200
% Foreign-born population	–0.7416	0.0081	0.2568	0.5096	1.1017	0.0800
% Female labor force participation	–0.3543	–0.2825	–0.2162	–0.1428	–0.0051	0.0200
% Other race population	–0.0101	0.2289	0.4972	0.8439	2.3171	0.0000
% Black population	0.1715	0.0080	0.0474	0.1183	0.2555	0.8000
Underemployment by low earnings						
Metro	–5.8630	–3.8343	–3.2352	–2.8342	–1.7211	0.2600
% Manufacturing employment	–0.2780	–0.1519	–0.0498	0.0614	0.1811	0.0000
% Services employment	–0.2062	–0.0434	0.1823	0.3600	0.5771	0.0000
% <High school education	–0.0766	0.0046	0.1153	0.2457	0.5009	0.0000

Table 7 continued

	Minimum	Lower quartile	Median	Upper quartile	Maximum	*P*-value Monte Carlo test
% College(+) education	–0.2220	–0.0494	0.1598	0.2234	0.5560	0.0100
% Female-headed families	–4.3155	–1.6437	–0.5104	0.3895	3.2808	0.1200
% Foreign-born population	–1.4245	–0.8511	–0.3847	–0.0539	0.7218	0.0200
% Part-time employment	0.1013	0.5091	0.7005	0.8712	1.0804	0.0000
% Female labor force participation	–0.4563	–0.3236	–0.2715	–0.1597	–0.0064	0.0000
% Other race population	–0.1746	0.2524	0.6529	1.2015	1.9172	0.0000
% Black population	–0.3558	–0.1271	–0.0415	0.0412	0.4189	0.3100

R-Squared values are greatest in the Dakotas and the manufacturing belt of Wisconsin.

The relationship between intermittent employment and manufacturing is positive in the global regression, while the local estimates show a significant and wide range of variation. The difference between the lower and upper quartiles is greater than twice the parameter's standard error—a rule of thumb suggested by Charlton et al. 2003 to identify significant nonstationary relationships (see Table 7, Fig. 4). There

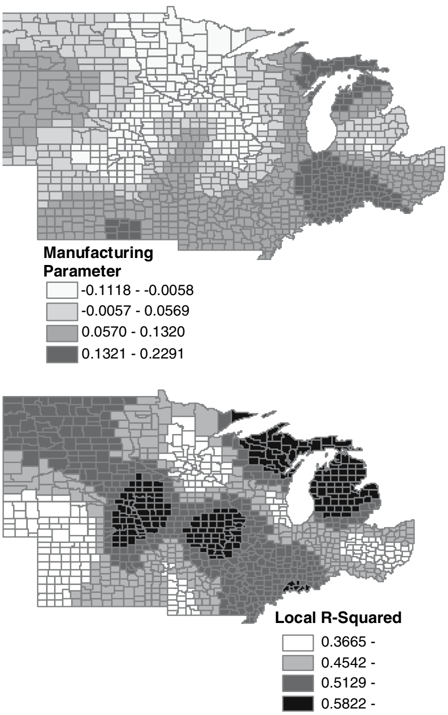

Fig. 2 GWR underemployment by low hours

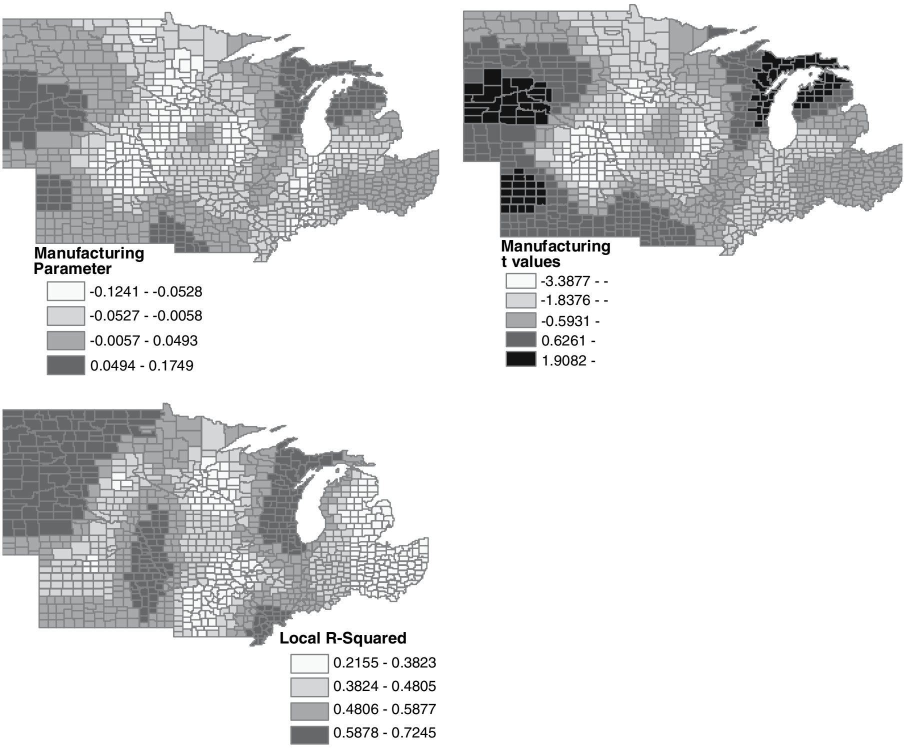

Fig. 3 GWR part-time employment

is a negative association between manufacturing and intermittent employment in the Upper Midwest and the Ozarks. It is interesting to look at the relationship between service jobs and intermittent employment, which is positive across all counties and noticeably larger than manufacturing, which supports the argument that many service jobs tend to be less stable in terms of work hours and weeks per year. Although the magnitude of the service coefficient changes, its relationship to intermittent employment is stationary and positive. In contrast, less than high school education, college education, female labor participation, and other race population exhibit a nonstationary relationship with intermittent employment. The model fits best in Michigan and northern Wisconsin, where the economic base is dependent on tourism and recreation.

The global regression indicates that low earnings are negatively associated with manufacturing, but the association changes in magnitude and direction across space as suggested by the GWR local estimates. The median local estimate is negative, but smaller than the global parameter, and in Michigan manufacturing employment is positively related to the percentage of working poor. In contrast, although the service coefficient is also negative in the global regression, its median local estimate is rather positive and large areas of the map conform to this pattern. There is also a nonstationary relationship between low earnings and service employment, education

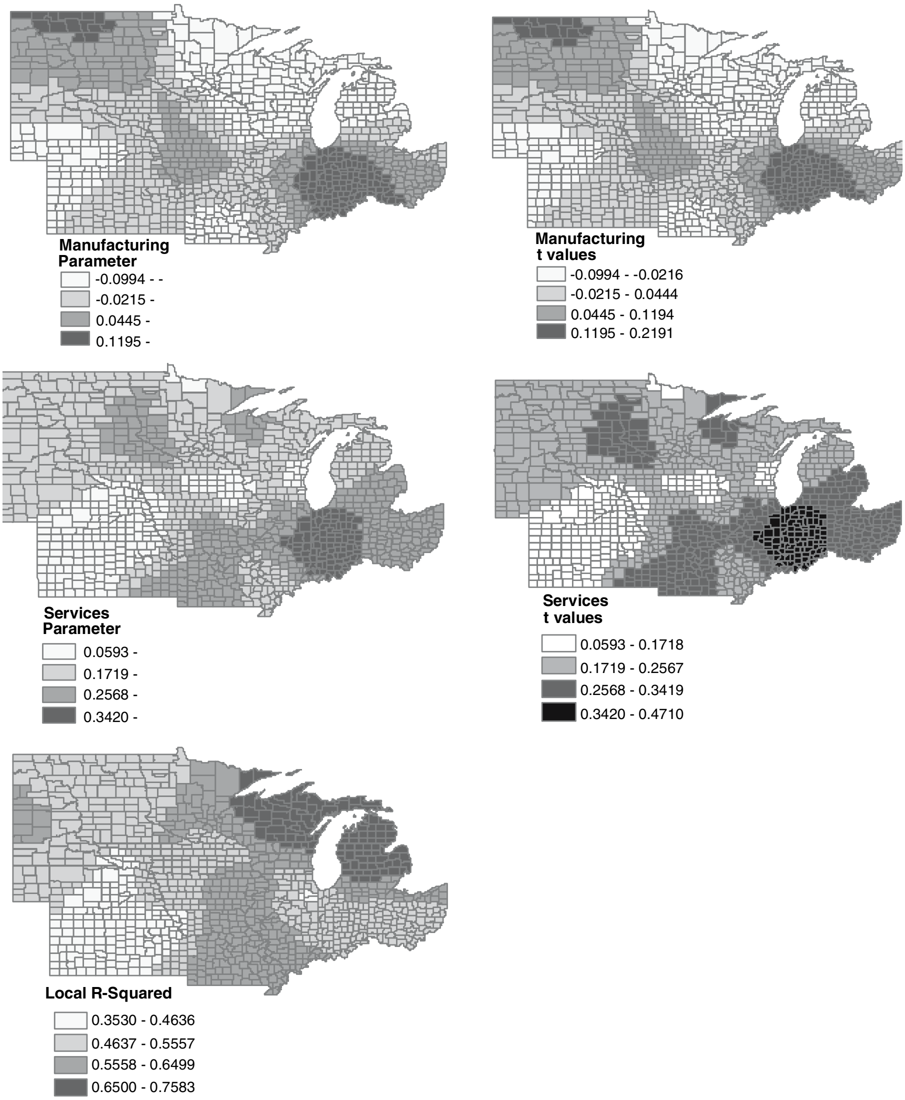

Fig. 4 GWR intermittent employment

variables, foreign-labor force, female labor participation, other race population and part-time employment.

It is important to notice that these variables do not exhibit the same spatial patterns. For example, places where less than high school education has a stronger negative effect are not the same places where service employment matters the most. As such, there is not an identifiable area where the relationships among our variables are unique from the rest of the Midwest.

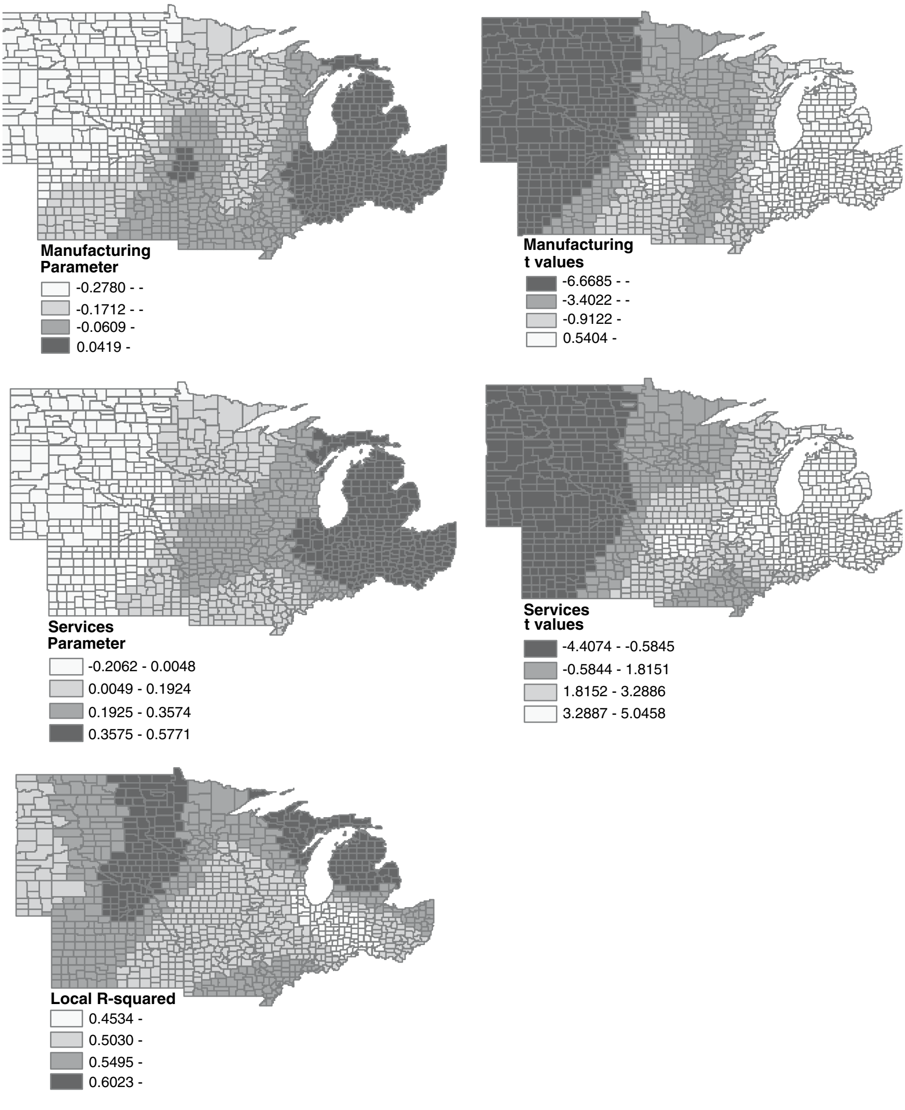

Fig. 5 GWR underemployment by low earnings

Discussion and Conclusions

The loss of manufacturing jobs has been well documented, but there has been little attention as to the effects of these processes across space. As we have suggested, this question should be addressed at the levels of both the individual and the local labor market area.

There are two major findings of note. First, we find that previous analyses that have looked at the effects of manufacturing employment on local economies may have overestimated the relationship because of spatial effects. When the effects of spatial dependence are controlled, the relationship between manufacturing employment and underemployment is weaker. In fact, manufacturing has a significant effect only on underemployment by low-earnings, but not on the other underemployment variables. The presence of spatial dependence in low earnings provides support for theories pointing out the reciprocal influences between local labor markets. Specifically, we have argued that manufacturing employment can affect labor market conditions in nearby locations through labor market standards and competition. This effect is present in income hardship, where manufacturing seems to be able to reduce the percentage of working poor beyond its location. However, there is no evidence of a significant effect on labor hardship associated with work time and steadiness. Although part-time employment exhibits substantive spatial dependence, manufacturing does not affect it; thus, the observed spatial pattern responds to other determinants such as service employment. It is important to highlight that low hours and intermittent employment show signs of spatial dependence in the error terms, which may be due to excluded variables that exhibit distinctive spatial patterns (Anselin 1992a). This analysis is taken at one point in time and it would be important to examine how these relationships have changed over the past few decades.

Second, the global weighted regression analysis revealed that the relationship between manufacturing employment and underemployment varied significantly across the Midwest. Manufacturing employment had a strong negative relationship with underemployment throughout much of the Dakotas and Nebraska, and a moderate effect in Wisconsin and Minnesota. Conversely, manufacturing employment was positively related to underemployment rates in Michigan, Illinois, Indiana, and Ohio. Overall, these findings suggest that in those areas in the Midwest that have historically had higher concentrations of manufacturing jobs, the relative benefits of working in this sector are smaller. In regions that have not had a large manufacturing sector and have experienced some gains in recent years, the benefits of working in the manufacturing sector are much larger.

This analysis suggests that it is important to take into consideration spatial effects when examining the implications of economic restructuring for regions. Labor market areas are not distinct spatial units and can be influenced significantly by nearby local labor markets. Our analysis demonstrates that the effects of industry and occupational structure may vary across local labor markets.

Beyond these methodological and theoretical issues, this analysis has some important policy implications. Although there has been a great deal of criticism of strategies for attracting manufacturing firms to areas that do not have a strong industrial base, the results suggest that they can have an important impact on the quality of jobs in a region. The economic restructuring process may bring some important benefits to these regions while creating more problems for regions that are more industrialized. These issues, however, need to be examined on a regional rather than a local basis.

Another policy issue that emerges is the regional nature of the impact of manufacturing. In most states the benefits of recruitment accrue only to the locality. Other localities in the region may actually pay more as a result of residential development. Regional strategies of sharing taxes and costs of development need to be more fully explored through spatial analysis.

Finally, several avenues of research are needed to explore these issues in more detail. Our focus in this paper has been on the entire manufacturing sector, but additional work needs to look at various subsectors to fully understand how manufacturing employment affects regional economies. For example, it may be useful to assess whether the core-periphery distinction continues to be important in this context. Another essential piece of this research would be to examine these issues over time. As the manufacturing sector has been restructured we might expect the spatial effects to decline over time. Yet, this is an empirical question that has received very little attention.

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