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REGIONAL LABOR FORCE CHARACTERISTICS AND RECENT SHIFTS IN THE LOCATION OF INDUSTRY

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ABSTRACT: *Regional variations in labor force characteristics have often been suggested as an explanation for recent interregional shifts in the location of American industry. This study explores the possibility of creating a model of industrial responses to regional labor force characteristics over relatively short time periods in a multiple regression framework using a variety of data on labor force characteristics available for large metropolitan regions. Calibration results suggest that regional labor force characteristics predict regional changes in industrial employment approximately as well as other reported predictors, and particularly influential predictors are identified. Contrary to hypotheses suggested in the literature, very little systematic variation is noted in calibration results across industries despite differences in typical firm size, vertical linkage patterns, growth or decline of the industries, or ratio of labor costs to value added.*

The selling and buying of workers' labor in the labor market is an essential aspect of the American capitalistic economic system and a fundamental element of daily survival in contemporary American society. The personal, individual reality of this imperative, the experience of salaried success, unemployed frustration, racial and gender discrimination, promotion and responsibility, the tense emotional confrontation of a strike, can never be captured in a set of numbers, an immutable equation. This personal, immediate reality, however, is only part of a larger set of processes determining the location of economic activity. These processes include the interplay of social forces and economic structures influencing levels of investment, rates of return on investment, circulation of investment capital, rates of investment in fixed capital assets (production assets), and the accumulation of capital. Many of these outcomes are linked in one way or another to labor market processes, which in turn are encumbered or facilitated, inhibited or promoted, by regional variations in labor force characteristics[1].

One objective of industrial location theory has been the development of a location model incorporating realistic aspects of labor market processes in such a way that the model would provide accurate predictions of interregional shifts in industrial activity and be useful in a variety of regional planning contexts and in the formulation of regional and national economic policy. With this goal in mind, the exact type of model to be developed must be carefully considered. Traditional theoretic models of industrial location are inappropriate for several reasons. Such models involve too many unrealistic assumptions, focus on artificially optimal distributions, and pay little attention to presently realistic process explanations[2].

More recent theoretic models of industrial location provide a more realistic alternative, but these models have shortcomings as well. The behavioral models impose a number of problematic methodological assumptions and fail to address the question of whether the rationales given for successful locational decisions are, in fact, the true reasons for their success. In addition, only the vaguest sketches have been proposed for a technique of generalizing from studies of locational decision-making algorithms to predictive behavioral models of aggregate interregional distributions of industrial activity. The structural models are very realistic and are particularly interesting for their focus on the condition of labor and on plausible labor market processes, but little effort has been made to mold these models into a form supplying specific detailed predictions of the sort required for applied regional planning and the formulation of regional and national economic policy.[3]

Many of the insights of all these types of industrial location models, and especially the emphasis on realistic labor market processes found in the structural models, can be incorporated in a multiple regression model of industrial location. Such a model could readily produce positive, detailed spatial predictions appropriate for planning or policy formulation, and through the careful selection of predictor variables, the model would reflect a realistic process explanation of interregional shifts in industrial activity. A carefully specified multiple regression model holds the promise of a substantial degree of utility in regional planning contexts and in the formulation of governmental economic policies. Alternative scenarios of future events could be explored with such a model, and the economic and regional implications of specific planning decisions and policy initiatives could be predicted.

A multiple regression model of industrial location based on labor force characteristics also permits, at least in theory, the inclusion of as many different predictor variables as necessary to represent the realistic operation of labor market processes. Each predictor variable is associated with a parameter, and the parameters can be tested for significance. In this way, the contribution of each predictor to the total model can be measured, and hypotheses concerning the importance of each predictor or combinations of predictors may be examined. When a considerable number of predictor variables are available, as is the case with labor force characteristics, stepwise regression techniques may be employed to evaluate the contribution of each predictor and incorporate only the most important predictors into the model. This reduces the effects of any multicollinearity inherent in the full data set and emphasizes the causal role of the most important predictors.

Another advantage of a multiple regression model of industrial location based on labor force characteristics is that it can be given either a structural or a behavioral interpretation. Ideally, we might wish that the model would weigh these two alternatives and indicate which is the more appropriate or describe the manner in which they complement each other, but the detailed theory required to support such an evaluation has yet to be developed. Until that detailed theory is devised, a multiple regression model of industrial location can be applied to planning and policy deliberations by practitioners and theorists favoring either a behavioral or a structural theory. From a structural interpretation, the parameters of a multiple regression model may be taken to represent contextually determinate (in political, economic, social, and technological terms) market process evaluations of the influence of labor force characteristics on industrial location. From a behavioral interpretation, the parameters represent a combination of the cognitive transformation (distortion) of the objectively measured predictor variables and the behavioral evaluation of those cognitively transformed variables.

THE PROPOSED MODEL

The US government regularly publishes a variety of statistics reflecting labor force characteristics. Much of these data can be incorporated in a multiple regression model of industrial location. Since we should expect different industries to react in different ways to similar labor force characteristics, separate equations should be estimated for each industry. The response variable of interest in each industry is the change in employment in that industry in a given region during a given time period. The predictor variables used to model the change in employment in each industry are a collection of regional labor force characteristics measured over the same time period. The model, then, will consist of a separate regression equation for each industry predicting the change in employment in any region[4].

Temporal Stability and Geographic Definition of Regional Labor Markets

The response variable in the proposed model, change in industrial employment, must occur over a period of time, but the appropriate period of time is not immediately obvious. The period must be long enough to allow an accumulation of change sufficient to smooth out very short-term fluctuations and permit the identification of longer-term trends. If the period is too short, the relationships established in the model will be misleading. Yet with constant changes in the economy, the model's estimated parameters cannot be expected to remain accurate over too great a length of time. If the period is too long, problems of parameter stability will be exacerbated by the likely presence of feedback processes between the predictor and response variables. By choosing a relatively short calibration period, the effects of these feedback loops are minimized, and the predictor variables can be treated as exogenous.

A calibration period of five years was selected in the belief that this period would be long enough to smooth out the most ephemeral economic fluctuations and yet be short enough to avoid the most pronounced feedback effects among the variables. With this relatively short calibration period, it was hoped that projection accuracy (parameter stability) would hold up for two future five-year prediction periods, giving the model's parameters a fifteen-year lifespan. Selection of a five-year calibration period was partially influenced by the five-year gap between successive appearances of the federal *Census of Manufactures*. While the *Census of Manufactures* collects much useful industrial data, its timing need not control the time period of the proposed model since very few of the required data are derived from that census. In practice, the model could be recalibrated annually (using calibration periods of any length) with the appearance of new employment data.[5]

The level of geographic disaggregation most appropriate for a model of industrial employment change based on labor force characteristics would delimit regions coinciding exactly with labor markets. The actual spatial limits of a labor market, however, are not that easy to ascertain. A labor market is shaped to a great extent through the distribution of metropolitan newspapers. The "help wanted" sections of these papers announce job openings and employment possibilities and play a very important role in connecting workers with jobs (Goodman, 1970). Commuting patterns and the size of the metropolis will also have an effect on the extent of the labor market and may in fact create constantly fluctuating and overlapping submarkets. Despite this ambiguity, the prevalence of job commuting and lengthy "journey-to-work" patterns indicate that labor markets are considerably larger than even the largest of municipalities. At the very least, a central city along with its closer suburbs must be included in a metropolitan labor market area. Counties, while larger than most municipalities, are still smaller than many labor market areas. County boundaries often separate central cities from suburbs and bedroom suburbs from more industrial suburbs. Entire states, on the other hand, are obviously too large to represent functional labor markets.

A closer approximation to spatial labor markets is provided by Metropolitan Statistical Areas (MSAs) and the former Standard Metropolitan Statistical Areas (SMSAs) (Berry et al., 1968). MSAs and SMSAs, usually composed of one or more counties surrounding a central city, are partially defined by commuting patterns and are large enough to include most of the job commuting focused on a central city and its suburbs. They also correspond more closely than other predefined geographical units to the reach of metropolitan newspapers and the influence of those papers on commuting patterns. Reflecting these correspondences, most of the measures of labor market characteristics collected by the federal government are published only for metropolitan regions coinciding in most cases with MSAs and SMSAs, although industrial employment statistics are available for individual counties.

Since the federally defined metropolitan regions offer acceptably close approximations to spatial labor markets and provide readily available data, these areas will be the geographic regions, or regional labor markets, utilized in the proposed model of industrial location based on labor force characteristics. Some of the data sets for the predictor variables have been published only for the thirty largest metropolitan regions in population in 1973. It is these thirty metropolitan labor markets which provide the data base for the proposed model, and since these published data sets commence with the 1972 data, the five-year period from 1972 to 1977 was selected as the time period to be modeled.[6]

Modeled Industries

Industrial employment is reported in the federally published *County Business Patterns* series by Standard Industrial Classification (SIC) categories at the two-, three-, and four-digit levels. For the purpose of modeling the geographic distribution of industries, it would be ideal to define industries as narrowly as possible (ie: at the four-digit level) and thereby capture their specific labor force requirements. The catch is that, as industries are defined more and more specifically, fewer and fewer establishments are classified as part of the industry, and where a defined industry contains only a small number of establishments, those establishments are likely to be found in only a few metropolitan regions. To insure an adequate geographic distribution of each industry to be modeled, the industries were selected at the SIC three-digit level.

Several considerations were borne in mind while selecting the industries to be modeled. First, the number of industries modeled had to be large enough to demonstrate effectively the expected variation of coefficients from industry to industry, yet not so large as to make the data gathering overly onerous. Four to eight industries seemed reasonable for these purposes. Five SIC three-digit industries were ultimately selected. These industries and their major products are listed in Table 1.

Second, in order to insure the representation of each industry across the range of labor markets sampled, industries were selected which had at least a moderately large number of establishments, sufficient to be represented in almost every metropolitan region at some level of activity (see Table 2, column 1).

Table 1. Selected Industries

SIC 232	Men's apparel OFFICIAL SIC TITLE: Men's, youth's, and boy's furnishings, work clothing, and allied garments MAJOR PRODUCTS: Men's shirts, trousers, sweaters, jackets, ties, and underwear
SIC 335	Nonferrous metal products OFFICIAL SIC TITLE: Rolling, drawing, and extruding of nonferrous metals MAJOR PRODUCTS: Sheet, plate, foil, tubing, pipes, and wire of copper, aluminum, brass, bronze, and other nonferrous metals
SIC 346	Metal forgings and stampings OFFICIAL SIC TITLE: Metal forgings and stampings MAJOR PRODUCTS: Forged or stamped metal components for automobiles, aircraft, appliances, machinery, and utensils
SIC 357	Office machines and computers OFFICIAL SIC TITLE: Office, computing, and accounting machines MAJOR PRODUCTS: Computers, typewriters, printers, calculators, cash registers, and other office equipment
SIC 367	Electronic components OFFICIAL SIC TITLE: Electronic components and accessories MAJOR PRODUCTS: Microprocessors, electron tubes, transistors, diodes, transformers, switches, circuit boards, antennae, and headphones

Third, an important hypothesis presented by Scott (1983a; 1983b; 1984) suggests that the intra-urban location of industries characterized by highly specialized, vertically disintegrated, small firms is strongly influenced by transfer costs. These industries would be expected, at least on the intra-urban level, to cluster around the locations of their linkages rather than to gravitate to maximally exploitable labor markets. On the inter-metropolitan level, as well, these industries should follow the distribution of their linkages, and the labor force model should show them to be responsive, not to their own labor demands, but to the labor demands of their linkage industries. For such industries characterized by small firms with strong vertical linkages, the model will produce spurious labor force relationships. These spurious equations are nevertheless empirically grounded through the vertical linkages, and they should provide predictions as accurate as those for industries more directly responsive to labor force characteristics. To explore this question of accuracy, industries with both a high and a low ratio of employees to establishments were selected (see Table 2, column 4).

Ideally, an effort should be made to model a pair of industries which are closely linked but have significantly different labor demands. Despite the difference in labor demands, they should produce very similar coefficients. Unfortunately, the need to work with SIC three-digit industries precluded a test of a pair of closely linked industries. The three-digit industrial categories are too internally diversified (see Table 1) to permit an appropriately detailed analysis of closely linked industries. At the same time, however, the presence, within a three-digit industrial category, of a more specific industry characterized by small firms closely linked to another industry characterized by large firms in a different three-digit category should be expected to reduce the predictive accuracy of the model in regard to the three-digit category encompassing the small-firm industry. Both SIC 346, metal forgings and stampings, and SIC 367, electronic components, include more specific industries characterized by small firms linked to large-firm industries in other three-digit industrial categories. Thus, it is expected that the predictive accuracy of the proposed model will be diminished for these two modeled industries.

Fourth, industries in which labor costs are high as a proportion of value added are likely to be more sensitive to labor force characteristics, or at the very least, to wage levels. This might suggest that the proposed model would exhibit greater predictive

Table 2. Sizes of Selected Industries, 1972-1977

	Industry	Employment (thousands) 1972 (1)	1977 (2)	Establishments 1977 (3)	Ratio of Employees to Establishments, 1977 (4)	Rate of Emp Change (trend: 1977 ÷ 1972) (5)
SIC 232	Men s apparel	363.4	364.5	3013	121.0	1.003
SIC 335	Nonferrous metal products	188.3	177.4	1002	177.0	0.942
SIC 346	Metal forgings and stampings	263.5	288.0	3715	77.5	1.093
SIC 357	Office machines and computers	208.4	259.3	1317	196.9	1.244
SIC 367	Electronic components	335.8	373.5	4455	83.8	1.112

SOURCE: US Department of Commerce, Bureau of the Census 1981 *1977 Census of Manufactures*, Vol I (Subject Statistics), General Summary -- Industry Statistics, Table 1.

accuracy for high labor cost industries. On the other hand, the model incorporates a number of labor force characteristics which quite possibly vary independently of wage rates, and in view of the greatly increased mobility of material and capital inputs, all industries are expected to respond fairly strongly to differences in labor force characteristics. To investigate this aspect of model accuracy, industries with high proportional labor costs and industries with low proportional labor costs were both selected (see Table 3, column 3).

Fifth, it might be presumed that growing industries, in their search for preferred locations for expansion, might be more sensitive than declining industries to regional labor force characteristics. Yet, on the other hand, an industry in decline might be expected as well to contract most rapidly in those regions with unfavorable labor force characteristics. To check for possible differences between growing and declining industries in their sensitivity to regional labor force characteristics, industries from both of these categories were included (see Table 2, column 5).

Response Variables

In order to remove the effects of economic fluctuations from the model and direct attention more specifically to the influence of interregional differences in labor force characteristics, the response variables (changes in employment) are stated as regional competitive shifts calculated as:

$$DIFEMPxxx_i = EMPxxx_i^{1977} - EMPxxx_i^{1972}\left[\frac{EMPxxx_{US}^{1977}}{EMPxxx_{US}^{1972}}\right]$$

where $DIFEMPxxx_i$ is the actual change in employment in SIC three-digit industry *xxx* over the five-year period from 1972 to 1977 in region *i*, the $EMPxxx_i$ variables are total employment in industry *xxx* in region *i* in the indicated year, and the $EMPxxx_{US}$ variables are total employment in industry *xxx* in the US expressed in thousands of employees for the indicated year. The response variables are, thus, expressed as deviations from the national employment trends in each industry rather than as absolute numbers. The national trends could easily be added back in, if desired, to determine absolute changes in employment, but with the national trends removed, the model focuses more precisely and emphatically on the consequences of interregional differences in labor force characteristics.

Predictor Variables

The predictor variables are a variety of regional labor force characteristics likely to be influential in determining changes in the location of industrial activity. These labor force characteristics reflect the sizes of the regional labor forces, the class, gender, and racial segmentation of the labor forces, the regional unemployment rates, the prevailing industrial wage rates, a measure of labor productivity, the levels of unionization, the prevalence of work stoppages, the average age and educational levels of the labor forces, and the presence or absence of a right-to-work law. All of the predictor variables, with the exception of the right-to-work law variable, may be measured both as average values over the modeled time period and as differences in value between the beginning and end of the modeled time period. Either or both forms of the predictors may enter the model.

All of the predictors in the proposed model were checked against all of the response variables to see whether a power function (or two other common transformations. a log function or an exponential function) might better approximate the form of the relationship than would a linear function. These possibilities were examined for each pair of predictor and response variables by computing the bivariatecorrelations resulting from a considerable range of possible functional relationships between the pair of variables. The functional relationships producing the highest bivariate correlations were noted, and these transformed predictors were used as the starting point for an alternative set of equations to be compared with the equations based on the untransformed predictors. Negative power transformations and the log transformation were considered inappropriate for the predictors measuring changes in labor force characteristics. Since these predictors could conceivably take on both positive and negative values, negative power transformations and the log transformation would introduce awkward functional discontinuities at zero.[7]

EVALUATING THE INDUSTRIAL LOCATION MODEL

Since the metropolitan regions which provide the data for the proposed model are the thirty largest metropolitan regions in population in 1973, the complete data set should properly be considered a statistical population rather than a sample. The regression parameters, thus, will be statistical population parameters, and it would be inappropriate to test hypotheses concerning their estimation in this particular case.[8] The overall performance of the proposed model, however, may still be evaluated.

Two statistics which may be derived for the evaluation of a multiple regression model, and which are not conceptually premised on the existence of a statistical sample or any particular distribution of the data, are the coefficient of multiple determination (R^2) and the residual mean square (s^2). The coefficient of multiple determination is interpreted as the proportion of the variation in the response which is accounted for by a model's predictor variables. The residual mean square may be interpreted as an approximate mean squared error of prediction, and its square root, the root mean square error (s), may be viewed as an approximate mean error of prediction. Since the data used to evaluate this model are a statistical population, the usual formula for s corrected for the degrees of freedom in a sample by placing the quantity $n - p$ in the denominator, where n represents the number of observations and p represents the number of parameters in the multiple regression equation, was replaced by a formula appropriate for a statistical population:

$$s=\sqrt{\frac{\sum (y_i-\hat{y}_i)^2}{n}}$$

where y_i represents the observed response for region i and $\hat{y}_i$ represents the response predicted by the model for region i. In selecting a set of predictors, then, it would be

Table 3. Proportional Labor Costs in Selected Industries, 1977

Industry		Labor Costs (millions of dollars) (1)	Value Added by Mfg (millions of dollars) (2)	Ratio of Labor Costs to Value Added (3)
SIC 232	Men's apparel	2340.1	4935.2	.474
SIC 335	Nonferrous metal products	2640.0	5902.3	.447
SIC 346	Metal forgings and stampings	4511.3	8913.4	.506
SIC 357	Office machines and computers	3948.8	9921.4	.398
SIC 367	Electronic components	4556.5	9259.6	.492

SOURCE: US Department of Commerce, Bureau of the Census 1981 1977 Census of Manufactures. Vol I (Subject Statistics), General Summary -- Industry Statistics, Table 1.

desirable to construct a model in which R^2 takes on relatively large values and s takes on relatively small values.

The SPSS forward selection procedure was used to add predictors one-at-a-time to each equation (two equations per industry, one with untransformed predictors and one with transformed predictors, making ten equations in all). In each step of the procedure, the predictor with the greatest absolute partial correlation with the response variable was entered into the multiple regression equation, and R^2 and s were calculated. Predictors, up to a limit of five in each equation, were kept in the model if they produced an increase of .05 or more in R^2 or a decrease of ten or more in s (cf Draper and Smith, 1981, pp 296-299). Examining each equation derived in this fashion, if the beta weight for any predictor was less than 0.200, that predictor was removed, R^2 and s were recalculated, and any improvement was noted. This procedure produced the equations and evaluative statistics summarized in Table 4.[9]

Only four untransformed predictors were included in the calibration equation for nonferrous metal products (SIC 335) because s attained a local minimum with the addition of the fourth predictor. All of the other calibration equations include five predictors.

Of the ten calibration equations summarized in Table 4, predictors reflecting the size of the labor force appear in six; productivity predictors, work stoppage predictors, age predictors, and predictors reflecting the participation of women in the labor force appear in five; unionization predictors and unemployment predictors appear in four; blue-collar predictors and predictors reflecting the racial segmentation of the labor force appear in three; wage predictors appear in two; predictors reflecting regional education levels appear in one; and the right-to-work predictor fails to appear in any equation.

Given the amount of interest and speculation in the effects of regional wage rate differentials and right-to-work laws, it is very interesting that these predictors enter so seldom into the calibration equations. The complete absence of the right-to-work predictor, even from the equations for the men's apparel industry, is particularly intriguing.[10] Wage predictors, so often mentioned as the explanatory regional variable in news accounts of industrial shifts or relocations, carry the intuitively expected negative signs in both of the equations for the nonferrous metal products industry (SIC 335), but fail to show up in any other equations.

Interpretation of the signs associated with many of the predictors reflecting various labor force characteristics is, in fact, complex and problematic. Predictors may enter into equations in their own right, or they may enter as surrogates for other variables for which data are unavailable, or these various effects may be mixed together. A particular labor force characteristic may be evaluated positively in the case of one industry and negatively in the case of another, or the evaluation may be multifaceted, combining both positive and negative considerations in ways which might vary from industry to industry or even within an industry. The predictors reflecting the size of the regional labor force, age, productivity, and work stoppages are all ambivalent in these calibration equations, bearing a direct relationship to the change in employment in some cases and an inverse relationship in others. The predictors reflecting unemployment, the participation of women in the labor force, and regional education levels are completely counterintuitive, carrying negative signs in every case.

Predictors reflecting the racial segmentation of the labor force, on the other hand, carry the intuitively expected positive sign in calibration equations for the men's apparel (SIC 232) and electronic components (SIC 367) industries. Blue-collar predictors, perhaps also serving as surrogates for the attainment of appropriate skill levels in certain segments of the labor force, enter positively into an equation for the nonferrous metal products industry (SIC 335) but negatively into both equations for the office machines and computers industry (SIC 357). An unionization predictor enters a calibration equation for the men's apparel industry (SIC 232) with a very unexpected positive sign, but the positive sign on an unionization predictor for the metal forgings and stampings industry (SIC 346) is, perhaps, unsurprising. Unionization predictors carry the expected negative sign in both equations for the nonferrous metal products industry (SIC 335).

In every case, the transformed predictors perform better than the untransformed predictors, as would be expected, and the coefficients of multiple determination (R^2), ranging from .523 to .709, are comparable to those reported for the previous multiple regression industrial location models (Wiljanen, 1997). While the root mean square errors (s) in Table 4 will serve as benchmarks for future research, they are sufficiently large to discourage the use of these equations in planning and policy formulation contexts.

Interestingly, in light of the considerations which went into selection of the modeled industries, the coefficients of multiple determination show little

Table 4. Calibration Results

Industry and Type of Predictors	Predictors and Signs of Associated Parameters	R^2	s
SIC 232 Men's apparel			
Untransformed	size of labor force (–), change in size of labor force (+), change in racial segmentation of labor force (+), change in productivity (–), change in unionization (+)	.531	834
Transformed	size of labor force (–), change in size of labor force (+), age (+), change in productivity (–), change in work stoppages (–)	.709	657
SIC 335 Nonferrous metal			
Untransformed	size of labor force (–), unemployment (–), wage (–), change in unionization (–)	.601	826
Transformed	size of labor force (–), unemployment (–), wage (–), change in blue-collar (+), change in unionization (–)	.653	785
SIC 346 Metal forgings and stampings			
Untransformed	size of labor force (+), gender segmentation of labor force (–), unemployment (–), change in work stoppages (+), change in education (–)	.584	1296
Transformed	size of labor force (+), unemployment (–), change in unemployment, (–)change in unionization (+), change in work stoppages (+)	.623	1232
SIC 357 Office machines and computers			
Untransformed	gender segmentation of labor force (–), productivity (+), change in blue-collar (–), change in work stoppages (+), change in age (+)	.523	2967
Transformed	gender segmentation of labor force (–), age (–), change in age, (+) change in blue-collar (–), change in work stoppages (+)	.656	2518
SIC 367 Electronic components			
Untransformed	gender segmentation of labor force (–), productivity (+), change in productivity (–), change in racial segmentation of labor force (+), change in age (+)	.580	1966
Transformed	gender segmentation of labor force (–), productivity (+), change productivity (–) change in racial segmentation of labor force (+), change in age (+)	.643	1812

systematic variation across industries. Among the equations based on untransformed predictors, R^2 ranges from .523 for the office machines and computers industry (SIC 357) to .601 for the nonferrous metal products industry (SIC 335), a difference of only .078. When the transformed predictors are used, R^2 varies from .623 for the metal forgings and stampings industry (SIC 346) to .709 for the men's apparel industry (SIC 232), a difference of only .086. Moreover, the ranking of industries within each of these ranges is different with no one industry in the top or bottom of both ranges.

Industries such as metal forgings and stampings (SIC 346) and electronic components (SIC 367), which are characterized by small firms vertically linked to large firms in other industries, were expected to show smaller coefficients of multiple determination due to the diverse locational pulls of the vertical linkages, and this result is achieved in the equations based on transformed predictors. The equations based on untransformed predictors, however, produce just the opposite result, suggesting that the locational pulls of the vertical linkages are either weaker or more homogeneous than expected.

While a declining industry, nonferrous metal products (SIC 335), shows greater sensitivity to labor force characteristics in the equations based on untransformed predictors than the two growing industries, office machines and computers (SIC 357) and electronic components (SIC 367), there is almost no difference between these three industries in the results reported for the equations based on transformed predictors.

Similarly, industries with a relatively low ratio of labor costs to value added, such as office machines and computers (SIC 357), were anticipated to respond less strongly to regional differences in labor force characteristics than an industry with a relatively high ratio, such as metal forgings and stampings (SIC 346). This result is achieved in the equations based on transformed predictors, but the opposite result is produced by the equations based on untransformed predictors, suggesting that regional differentials in labor force characteristics are not necessarily more critical to industries with high proportional labor costs. Interestingly, the labor productivity predictor incorporating regional differentials in labor costs entered into the equation based on untransformed predictors for the office machines and computers industry (SIC 357) rather than into the equation for the more labor cost intensive metal forgings and stampings industry (SIC 346).

SUMMARY OF FINDINGS

The calibration results suggest that regional labor force characteristics predict regional changes in industrial employment approximately as well as any other predictors used in previously reported models. The labor force characteristics most often entering the calibration equations as predictors are the size of the labor force, levels of productivity, work stoppage activity, unionization, unemployment, the participation of women in the labor force, and the age of the labor force. It is particularly notable that regional wage rates seldom enter the calibration equations as predictors, and the presence or absence of a right-to-work law never shows up as influential. The signs associated with predictors are in many cases not what might have been expected when each predictor is given a simple, straight-forward meaning, but the interpretation of signs associated with predictors in a model such as this can be very complex. Very little systematic variation is noted in calibration results across industries despite differences in typical firm size, vertical linkage patterns, growth or decline of the industries, or ratio of labor costs to value added.

The considerable ambiguity in all of these results suggests that much more needs to be done along several distinct but related lines of research before we can produce a model of industrial employment based on labor force characteristics which we, as geographers, economists, planners, and theorists, can confidently turn to for accurate near future forecasts of industrial location.

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ENDNOTES

[1]Geographers who have examined these processes at length and considered these various linkages and interactions prominently include Harvey (1982), Scott (1988), and Storper and Walker (1989). The present work, while drawing insight and inspiration from these earlier studies, proceeds along a somewhat different path of research.

[2]Refer to Wiljanen (1997) for a review of the literature and a more detailed discussion of the difficulties of putting the traditional theoretic models of industrial location to practical usage.

[3]Wiljanen (1997) supplies examples and citations.

[4]A review and critique of earlier multiple regression models of industrial location is provided by Wiljanen (1997).

[5]Unfortunately, the slow dissemination of governmentally collected data insures that the model will always be calibrated with a data set already several years old. The arbitrary five-year calibration period should be readily revised as new data sources become available or theoretical and empirical research suggest a more appropriate time span. As the calibration period is adjusted in future revisions of this model, additional corrections may and should be made in the model's structure, providing for feedback loops and the simultaneous determination of a number of the variables and for a time-series, or longitudinal analysis of the model's parameters.

[6]The thirty metropolitan regions providing data for the proposed model are: Anaheim, Atlanta, Baltimore, Boston, Buffalo, Chicago, Cincinnati, Cleveland, Dallas, Denver, Detroit, Houston, Indianapolis, Kansas City, Los Angeles, Miami, Milwaukee, Minneapolis, Nassau (NY), New York, Newark, Philadelphia, Pittsburgh, Riverside, St. Louis, San Diego, San Francisco, San Jose, Seattle, and Washington. Details of the definitions of these metropolitan regions are contained in Wiljanen (1997).

[7]A full definition of all the predictor variables along with relevant discussion may be found in Wiljanen (1997).

[8]In addition, two issues which often arise in the development of spatial multiple regression models, the issues of spatial autocorrelation and statistical outliers, are not pertinent here. Since the calculated regression parameters will be statistical population parameters, there is no issue of regression estimates being biased due to spatial autocorrelation or statistical outliers.

[9]The full set of model equations and a more expansive discussion of the calibration results are provided in Wiljanen (1997).

[10]A richly argumentative literature has developed concerning the effects of right-to-work laws and the signs to be expected when right-to-work predictors appear in multiple regression models. A good point of entry into this discussion is offered by Moore and Newman (1985).

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