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Right-to-Work Laws and Manufacturing Employment: The Importance of Spatial Dependence

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Using 2000 decennial census data, we estimate the relationships between right-to-work (RTW) laws and employment in manufacturing and other industries. Estimates that do not account for geographically correlated omitted factors dramatically overstate the positive relationship between RTW legislation and manufacturing employment. We estimate that RTW legislation is associated with an increase in manufacturing's share of private wage and salary employment of 2.12%, an estimate almost 30% lower than the estimate that does not control for these spatially correlated omitted factors. Results for other industries indicate that RTW legislation is negatively associated with employment shares in the agriculture, forestry, fishing and hunting, and mining industries and some service industries, but is positively associated with employment shares in the information and professional, scientific, management, administrative, and waste management services industries. Improperly controlling for geographic factors can lead to incorrect inferences and misinform policy.

JEL Classification: C21, J58

1. Introduction

Right-to-work (RTW) laws prohibit the requirement that a person become a union member as a condition of employment. Such a prohibition, if effective, raises the cost of union organizing activity, leading to a decline in union membership and thus in union bargaining power. To the extent that this reduction in the bargaining power of unions occurs, firms considering locating in an RTW state may expect lower wages and a more favorable business climate than would be the case in a non-RTW state, leading to greater employment in RTW states, all else equal. Therefore, it is important to determine whether these laws are effective. 1

Many studies have documented a negative correlation between RTW laws and unionization rates, suggesting that RTW laws do indeed decrease unionization rates, although some of this correlation is thought to be due to negative public perceptions of unions in right-to-work states rather than the effect of the laws themselves. There have also been a few studies that have investigated the effects of RTW legislation on the level of and growth in manufacturing employment, but the results of these studies are mixed, with the results hinging

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on the particular econometric specification used. A regression of the manufacturing employment share on an RTW dummy variable often suffers from omitted variable bias, and each study attempts to deal with this bias differently. Potential omitted variables are climate, soil quality, the availability of natural and labor resources, infrastructure, and public attitudes toward unions and business, all of which are thought to be determinants of employment but are not easily measured. If public attitudes are probusiness, then omitting measures of public attitudes may positively bias the RTW coefficient. This is because probusiness attitudes may lead both to passage of RTW legislation and to other probusiness policies that increase employment. Another example may be the percentage of the population that consists of recent immigrants. Businesses that employ recent immigrants may be more likely to vote for RTW legislation and may employ more people. In addition, there may also be spatial correlation in the errors, because these omitted variables are likely correlated across counties. Weather, resources, infrastructure, and public attitudes usually do not change abruptly at political borders, and therefore these omitted factors would necessarily be geographically correlated. Another possibility is that manufacturing employment itself may be correlated across counties as a result of agglomeration economies, which are cost savings that result when firms locate in close proximity to one another. For example, firms may locate close to bodies of water such as rivers to take advantage of natural shipping routes, and any variables associated with firm activities would be geographically correlated. Finally, measurement error is also a possibility if the relevant unit of measurement is the city but we are measuring our variable at the county level.[1] The potential presence of omitted variables bias and spatial dependence and the techniques used to address them are the primary concern of this paper.

As will be seen in the literature review below, manufacturing has been the primary industry of interest with respect to analyzing the effects of RTW legislation because of the high percentage of manufacturing workers that are unionized. However, manufacturing is not the most unionized industry. According to www.unionstats.com, several other industries, including construction and transportation, were more highly unionized than manufacturing in 2000. Therefore, this analysis will also investigate the relationships between RTW laws and employment in several different industries.

2. Literature Review

Three early studies of the effects of RTW legislation on employment are discussed in two literature reviews by Moore and Newman (1985) and Moore (1998). The first study by Soffer and Korenich (1961) took a simple analysis of variance approach and concluded that RTW laws do not contribute to the expansion of a state's nonagricultural jobs and industrial development. However, this model ignored the influence of factors other than RTW laws on employment in a state. A later study by Newman (1983) used multiple regression analysis to control for variables thought to be important determinants of employment to find a significant positive relationship between RTW legislation and relative changes in employment, particularly for labor-intensive industries. The third paper, also by Newman (1984), demonstrated the existence of RTW effects and also that they diminished over time and eventually disappeared.

[1] Anselin (1988, p. 12) provides an example of measurement error.

However, both of Newman's studies likely suffered from omitted variables bias. In addition, none of these early studies addressed spatial autocorrelation in either the dependent variable or the error term.

Later studies have attempted to address these issues, however. Perhaps the most significant attempt to deal with the problem of omitted variables bias due to the exclusion of unmeasurable geographic characteristics was made by Holmes (1998). He defined the problem as one of distinguishing the effects of state policies from the effects of other state characteristics unrelated to policy, and proposed that the solution is to analyze what happens at the border of two counties, one in an RTW state and the other in a non-RTW state. As Holmes noted, if state policies are an important determinant of the location of manufacturing, one should find an abrupt change in manufacturing activity when one crosses a state border at which policy changes. This is because state characteristics unrelated to policy are likely to be the same on both sides of the border. Thus, Holmes' approach was to focus on border counties in his analysis.

Holmes used two measures of manufacturing activity: manufacturing employment in a county as a percentage of total private nonagricultural employment in the county, taken from 1992 County Business Patterns (CBP) and Census of Manufactures data, and the growth rate in manufacturing employment over the postwar period from 1947 to 1992. Holmes regressed manufacturing's share of total private employment on an RTW dummy and two distance functions to control for a county's proximity to an RTW border and the side of the border on which a county is located. Holmes generated and analyzed several specifications of the geographic functions and found that controlling for geography affected the estimated RTW coefficient. Holmes found that when one crosses the border into the RTW state, the estimated average increase in manufacturing share was approximately 6.6%, an estimate about one-third higher than the estimate that did not control for geography.

Although Holmes dramatically improved controls for unmeasured geographic factors, his use of ordinary least squares (OLS) to estimate the regression coefficients and standard errors may have been inappropriate. Holmes did not consider that the dependent variable itself may have been spatially correlated because of agglomeration economies or measurement error or that the residuals were spatially correlated. If OLS is used to estimate a model where the dependent variable is spatially correlated, the resulting coefficient estimates will be biased and inconsistent. On the other hand, if there is evidence of spatial correlation in the residuals of an OLS regression, the top estimator will be unbiased but inefficient.[2] The distance functions used by Holmes are also a concern, as they may have only crudely approximated geographic reality (see Barry, Pace, and Sirmans 1998). If this is the case, Holmes' error terms across counties were still likely correlated.

Two studies since Holmes' have attempted to address the issues of omitted variables bias and correlated errors but have been limited in scope, focusing on only one RTW state, Idaho, and on the growth in manufacturing employment after the implementation of an RTW law rather than on the level of manufacturing employment at a point in time. Wilbanks and Reed (2001) investigated the effects of RTW legislation on manufacturing employment in Idaho following that state's adoption of an RTW law in 1986. They performed a county-level analysis but did not use Holmes' technique to control for geographic factors, instead making comparisons based on alternative treatment and control groups, and found that manufacturing employment growth was significantly greater in Idaho than in the control groups. Unlike

[2] Anselin (1988) provides all of the appropriate mathematical derivations.

Holmes, they included several variables to control for demographic and geographic characteristics such as measures of educational attainment, population growth prior to the adoption of RTW legislation, the share of the population that is black, measures of industry composition, and dummy variables indicating the urban or rural status of a county. Although not directly concerned with spatially dependent errors, they did attempt to address heteroskedasticity concerns caused by their dependent variable and concerns about the independence of the error terms across observations using robust cluster estimation, where the clusters appeared to be Bureau of Economic Analysis Economic Areas in some specifications and states in others. However, the potential for spatially correlated errors remained, as these cluster analyses allowed for correlation in the error terms within clusters but not across clusters. In addition, their analysis did not control for agglomeration economies or measurement error by allowing the dependent variable to be spatially correlated across counties.

Dinlersoz and Hernandez-Murillo (2002) also attempted to determine the effects of RTW legislation on Idaho's industrial performance as measured by employment growth. Their method of controlling for geographic factors was similar to that of Wilbanks and Reed (2001) in that they used neighboring states as controls for common region-specific factors. They found that postlaw, Idaho experienced a significant and persistent annual growth in manufacturing employment compared to almost zero growth in manufacturing employment in neighboring states. They also found that the difference between prelaw and postlaw growth rates in Idaho was significantly larger compared with other states in the region. However, they did not include demographic controls, nor did they address correlation in the error terms or in the dependent variable across counties.

This paper attempts to improve upon the existing literature on the relationship between manufacturing employment and RTW laws by better controlling for omitted factors that may be spatially correlated. In particular, correlations across counties in the error term and in the dependent variable are separately addressed. In addition, several county-level demographic characteristics likely to affect the supply of or the demand for labor or to reflect public attitudes or tastes regarding state policies are included. These variables describe the age distribution, race and ethnic composition, gender composition, and educational level of a county's population as well as measuring the degree of urbanization or population density. The paper also improves upon the existing literature by exploring the relationships between RTW laws and employment in other industries besides manufacturing.

3. Model and Estimation Technique

As noted above, many studies of RTW legislation fail to adequately control for unobserved factors that may vary systematically over space or for possible spatial dependence in the dependent variable, a phenomenon known as spatial autocorrelation. Spatial autocorrelation may be formally defined as follows (Anselin and Bera 1998, p. 241):

$$\mathrm{Cov}(y_i, y_j) = E(y_i, y_j) - E(y_i)E(y_j) \neq 0 \text{ for } i \neq j$$

where y_i and y_j are observations on a random variable at locations i and j in space. The subscripts i and j can refer to states, counties, or any other geographic designation. The important point is that the observations are correlated across space. Why might we see such correlation across observations in space? One reason mentioned earlier with respect to employment is agglomeration economies, with firms wishing to locate near other firms for cost savings. It may be the case that there are ''employment centers'' in one county that draw employees from surrounding counties. Alternatively, measurement error may also cause random variables to be spatially correlated if a city is the relevant unit of measurement but we are measuring our variable at the county level. In either of these cases, employment is correlated across counties. It is also possible that omitted variables such as climate or political attitudes that are difficult or impossible to measure may be correlated across counties. For example, a cursory look at the so-called red/blue county map showing support for the two main political parties in the most recent presidential election bears this out.[3]

When the dependent variable is spatially correlated, as when employment is due to agglomeration economies, employment centers, or measurement error, we can use what Anselin (1988, p. 35) refers to as a mixed regressive–spatial autoregressive model given by

$$y = \rho Wy + X\beta + \varepsilon \tag{1}$$

$$\varepsilon \sim N(\sigma^2, I_n)$$

where y contains an $n \times 1$ vector of the percentage employment in manufacturing or other employment variable in a county, X is an $n \times k$ matrix of several demographic control 2
variables as well as an RTW dummy variable, ε is an $n \times 1$ error term, and ρ and β are the coefficients to be estimated. The W term represents a first-order spatial weight matrix, ''which expresses for each observation (row) those locations (columns) that belong to its neighborhood set as nonzero elements'' (Anselin and Bera 1998, p. 243).[4]

It is important to note that the inclusion of the Wy term on the right hand side of Equation 1 introduces simultaneity bias, and therefore the use of OLS as an estimation strategy will produce biased and inconsistent parameter estimates (Anselin 1988, pp. 57–59). Therefore, maximum likelihood estimation is used to estimate the parameters in the mixed regressive–spatial autoregressive model. The log likelihood for the model expressed in Equation 1 under the assumption of normally distributed error terms, ε, and homoskedasticity is given by Anselin (2001, p. 320):

$$\ln L = -(n/2)\ln(2\pi) - (n/2)\ln\sigma^2 + \ln|I - \rho W| - (1/2\sigma^2)(y - \rho Wy - X\beta)'(y - \rho Wy - X\beta)$$

The key coefficients of interest are ρ and the coefficient on the RTW dummy variable, as we are interested in whether or not spatial dependence exists and in the relationship between RTW legislation and the employment variable of interest. In particular, if ρ is statistically significantly different from zero there is spatial dependence, suggesting that agglomeration economies, employment centers, or measurement error in the dependent variable exists. If the RTW coefficient is greater than zero, then RTW laws are positively associated with employment. Alternatively, if the RTW coefficient is less than zero, RTW laws are negatively associated with employment. Henceforth, the mixed regressive–spatial autoregressive model will be referred to as the SAR model.

[3] For a graphical depiction of this county map, please see http://www.usatoday.com/news/politicselections/vote2004/countymap.htm.

[4] An excellent introduction to spatial econometric techniques can be found in LeSage (1997). All MATLAB code used to estimate the models in this paper is available from Jim LeSage's website, found at www.spatial-econometrics.com.

A second type of spatial dependence involves correlation across the error terms. It is possible that when an econometric model is specified and estimated, there may be variables that are omitted. With respect to the determinants of employment, such omitted variables may include natural resources or infrastructure, public attitudes towards unions and/or businesses, and/or labor supply characteristics. These omitted variables are usually subsumed into the error term and thus may bias the RTW coefficient. If public attitudes are probusiness, then omitting measures of public attitudes may positively bias the RTW coefficient. This is because probusiness attitudes may lead both to passage of RTW legislation and to other probusiness policies that increase employment. Another example may be the percentage of the population that consists of recent immigrants. Businesses that employ recent immigrants may be more likely to vote for RTW legislation and may employ more people. Hence, in this case as well the RTW coefficient may be biased upward. If these omitted variables vary in a systematic manner over space, there may also be spatial error dependence. For example, a supply of natural resources may exist beyond the boundary of a single county. Alternatively, public attitudes and/or characteristics of the supply of labor may be similar across county lines. Anselin (1988, p. 35) defines this as the linear regression model with a spatial autoregressive disturbance. It is given by:

$$\begin{aligned} y &= X\beta + u \\ u &= \lambda W u + \varepsilon \\ \varepsilon &\sim N(0,\sigma^2 I_n) \end{aligned} \tag{2}$$

where β is defined as before but now there is no spatially weighted y term on the right hand side and the error term is now specified by u. In this model, the key coefficients of interest are λ and the coefficient on the RTW dummy variable. $\lambda \neq 0$ implies that the errors are spatially correlated, and a positive RTW coefficient again indicates that RTW laws are positively associated with the employment variable. Estimation of this model via OLS results in parameter estimates that are unbiased (as long as the omitted variables are uncorrelated with the other included explanatory variables) but inefficient, so maximum likelihood techniques are used. Anselin (2001, p. 320) provides the following log likelihood function under the assumption of normally distributed error terms, ε, and homoskedasticity used in estimating the spatial error model:

$$\begin{aligned} \ln L = &-(n/2)\ln(2\pi) - (n/2)\ln\sigma^2 + \ln|I - \lambda W| \\ &- (1/2\sigma^2)(y - X\beta)'(I - \lambda W)'(I - \lambda W)(y - X\beta) \end{aligned}$$

The $\lambda W u$ term in Equation 2 uses the same row stochastic spatial weight matrix W used in the first model, but now it defines the contiguity relationship among the error terms. Henceforth, the model with a spatial autoregressive disturbance is referred to as the SEM model.

4. Data

RTW legislation is thought to make it harder for unions to organize and thus weakens their bargaining power, potentially leading to an increase in employment in heavily unionized sectors. One such heavily unionized sector is manufacturing.[5] Because of its high level of unionization and the heavy emphasis on manufacturing employment in previous studies, the primary focus of this paper is also manufacturing employment. We define our key dependent variable to be manufacturing employment as a percentage of total private wage and salary employment in a county in 2000. We choose to investigate employment at a point in time because of the cross-sectional nature of the models used to deal with spatial correlation and the economic question of whether or not RTW laws still matter many years after their passage, and also because previous studies have focused on this variable. However, we also investigate alternative dependent variables, including the number of manufacturing employees in 2000, manufacturing employment as a percentage of total employment (not just private), and, to a lesser extent, the growth rate in manufacturing over the 1947–1997 period, to determine whether results are sensitive to the way the manufacturing employment variable is defined. The data used to construct all the point-in-time variables were taken from the 2000 Decennial Census Profile of Selected Economic Characteristics. The data used to construct the growth rate were taken from various issues of the City and County Data books that are available online from the University of Virginia's Geospatial and Statistical Data Center.[6] Only 194 observations were available for the growth rate model because of missing data.[7] As mentioned earlier, we employ standard spatial econometric techniques and estimate only cross-sectional models. Spatial panel data models and methodologies do exist (for example, see Elhorst 2003), but we do not employ them here for two reasons. First, the demographic data are unavailable for the appropriate sample period. Second, the weight matrix, W, is assumed to remain constant over time, which would pose problems for our county level sampling technique given that counties have been added or otherwise changed over the years[8].

Manufacturing, however, is not the most highly unionized industry. According to www.unionstats.com, other industries with higher percentages of employees covered by unions in 2000 were forestry, metal and coal mining, construction, transportation, communications, utilities and sanitary services, theatres and motion pictures, educational services associated with elementary and secondary schools, legal services, labor unions, and public administration. Although industries are grouped differently by www.unionstats.com than they are in the Economic Profiles, we do analyze employment in other industries in order to investigate 3
whether RTW laws play a role in any other highly unionized industries and perhaps even affect industries that are not very unionized. The industries we consider include: agriculture, forestry, fishing and hunting, and mining; construction; wholesale trade; retail trade; transportation and warehousing and utilities; information; finance, insurance, real estate, and rental and leasing; professional, scientific, management, administrative, and waste management services; educational, health, and social services; arts, entertainment, recreation, accommodation, and food services; other services (except public administration); and public administration. For each of these industries we examine the number of employees and industry employment as a percentage of total employment.

The key explanatory variable is an RTW dummy variable equal to one if a state is an RTW state and equal to zero otherwise. Issues from 1998 through 2003 of the *Monthly Labor*

[5] Data on unionization rates are available from www.unionstats.com.

[6] Please see http://fisher.lib.virginia.edu/collections/stats/ccdb for details.

[7] A number of growth rate models were estimated using different growth measures and different measures of manufacturing employment. Regardless of the methodology used to calculate the growth variable, the results were similar.

[8] One example is the creation of Cibola County, NM, which was created in part by taking land from Valencia County, NM on June 19, 1981. Please see http://www.census.gov/geo/www/tiger/ctychng.html for further examples.

Review (U.S. Bureau of Labor Statistics 2004) that provide yearly updates on state labor legislation were checked to ensure the accuracy of the list of RTW states. Although there were 22 RTW states in 2000, only 14 of these states, Arizona, Arkansas, Idaho, Iowa, Kansas, Nebraska, Nevada, North Dakota, South Dakota, Tennessee, Texas, Utah, Virginia, and Wyoming, are used in this analysis because they are the only ones that border at least one non-RTW state. The non-RTW states that border the RTW states used in our sample are California, Colorado, Illinois, Kentucky, Maryland, Minnesota, Missouri, Montana, New Mexico, Oklahoma, Oregon, Washington, West Virginia, and Wisconsin.

Earlier studies have noted that it is difficult to distinguish between the effects of an RTW policy and other probusiness policies (see, for example, Holmes 1998). In an attempt to distinguish between the effect of RTW legislation and just a generally business-friendly climate, a Small Business Survival Index (SBSI) obtained from the Small Business & Entrepreneurship Council is included along with the RTW dummy in the manufacturing employment share regressions presented in this paper. A higher value for this index means a less friendly business climate. The existence of an RTW law was netted out of this index in order to obtain a measure of other probusiness policies and/or public attitudes toward unions. This index is comparable to the FANTUS index that Holmes used, but the SBSI is much more recent than the FANTUS ranking.[9] 4

The SBSI may be an imperfect measure of business climate, however, so there may still be omitted variables bias. One technique for dealing with omitted variables bias is to include as many relevant regressors on the right-hand side of a regression as are available. Therefore, several other county-level population characteristics are included as explanatory variables to control for characteristics of a county's labor supply and for public attitudes towards unions or business in general that, if omitted, might bias the RTW coefficient. These include the size of the population, the percentage of the population aged 18–64, the percentage of the population aged 25 and over whose highest level of educational attainment is a bachelor's degree, the percentage of the population that is female, the percentage of the population that is Hispanic, the percentage of the population that is nonwhite, the percentage of the population that speaks a language other than English at home, the population per square mile, and the mean travel time to work for individuals aged 16 and over. The spatial techniques we use to control for spatially correlated omitted variables also help eliminate omitted variable bias, at least that portion due to spatially correlated omitted variables. Although we cannot be certain that we have eliminated all omitted variables bias, we believe we have made greater progress than previous studies in controlling for omitted variables.

Table 1 provides the descriptive statistics for the variables used in the analysis. Note that, on average, manufacturing accounted for over 18% of a county's private wage and salary employment in 2000 and that just over 52% of the border counties were located in RTW states. Data sources are contained in the Appendix.

5. Results

Table 2 shows the estimated relationships between manufacturing as a percentage of private wage and salary employment and the existence of an RTW law in a state in 2000. These

[9] The FANTUS ranking and the SBSI are similar measures. However, the FANTUS ranking is from 1975 whereas the SBSI is from the year 2000.

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Table 1. Descriptive Statistics for Variables ($N = 427$)

Variable Description[a]	Mean	Minimum	Maximum	Standard Deviation
Manufacturing employment	2728.21	2	84,166	6674.80
Manufacturing employment as a percentage of private wage and salary employment	18.441	0.717	46.176	11.467
Manufacturing employment as a percentage of total employment	13.40	0.398	35.217	8.915
Growth rate in manufacturing employment 1947–1997[a]	1983.43	−92.65	56,208.33	5997.14
Agriculture, forestry, fishing and hunting, and mining employment	759.95	61	13,063	918.52
Agriculture, forestry, fishing and hunting, and mining employment as a percentage of total employment	10.83	0.16	56.66	9.08
Construction employment	1804.27	17	62,115	5472.19
Construction employment as a percentage of total employment	7.46	2.17	20.41	2.37
Wholesale trade employment	736.71	2	27174	2258.10
Wholesale trade employment as a percentage of total employment	2.81	0.52	7.23	1.07
Retail trade employment	2844.96	13	84,460	8102.52
Retail trade employment as a percentage of total employment	11.32	3.10	26.90	2.34
Transportation and warehousing employment and utilities employment	1280.88	15	46,776	3864.32
Transportation and warehousing employment and utilities employment as a percentage of total employment	5.70	1.64	17.25	1.74
Information employment	757.19	0	36,721	3041.98
Information employment as a percentage of total employment	1.79	0	10.23	1.05
Finance, insurance, real estate, and rental and leasing employment	1425.68	0	43,631	4805.91
Finance, insurance, real estate, and rental and leasing employment as a percentage of total employment	4.22	0	14.16	1.63
Professional, scientific, management, administrative, and waste management services employment	2183.40	0	112,036	9145.03
Professional, scientific, management, administrative, and waste management services employment as a percentage of total employment	4.68	0	23.47	2.64
Educational, health and social services employment	4620.04	29	140,063	12,873.09
Educational, health and social services employment as a percentage of total employment	20.32	6.55	45.06	4.58
Arts, entertainment, recreation, accommodation, and food services employment	2278.59	8	191,596	10,629.06

Table 1. Continued

Variable Description[a]	Mean	Minimum	Maximum	Standard Deviation
Arts, entertainment, recreation, accommodation, and food services employment as a percentage of total employment	7.36	1.14	30.06	3.90
Other services (except public administration) employment	1229.29	10	34,428	3827.73
Other services (except public administration) employment as a percentage of total employment	4.83	1.84	8.08	1.01
Public administration employment	1533.36	17	65,619	5838.18
Public administration employment as a percentage of total employment	5.27	1.58	26.92	3.05
Percentage of population aged 18–64	58.645	48.5	79	4.106
Percentage of population aged 25 or above with a bachelor's degree	15.948	5.4	60.2	7.375
Percentage of population who are female	50.331	37.2	55.6	1.738
Percentage of population who are Hispanic or Latino	7.931	0.1	78.2	13.059
Percentage of population age 25 or above who are high school graduates or higher	77.810	46.1	95.3	8.920
Percentage of the population nonwhite	11.24	0.3	83.6	12.387
Percentage of population that speaks language other than English at home	9.446	1.1	74.1	12.24
Persons per square mile	81.168	0.3	7323.3	403.157
Small business survival index	41.285	24.88	52.15	7.024
Mean travel time to work in minutes for persons age 16+	21.299	10.8	39.7	5.45
Right to work (RTW) dummy variable	0.522	0	1	0.5

[a] All data are for 2000 except for growth rate in manufacturing employment 1947–1997.
[b] Based on 194 observations instead of 427 because of missing values.

estimates are based on data for the 427 counties that lie on the borders between RTW and non-RTW states. Results for three different specifications are shown. The first column of results shows the OLS estimates and the second and third columns of results show those from the SAR and SEM models, respectively. Recall that the SAR and SEM models apply spatial techniques and are estimated via maximum likelihood.

The OLS coefficient on the RTW dummy variable in Column 1 is positive and statistically 6
significant at the 1% level, indicating that states with right to work laws have higher manufacturing employment by over 3% on average, all else equal. The estimated SAR coefficient on the RTW dummy variable in Column 2 is also positive and significant at the 5% level, but the estimated effect is much smaller at 1.63%. Note that the estimated ρ is positive and highly significant, indicating the existence of spatial dependence. The estimated SEM coefficient on the RTW dummy variable in Column 3 is also positive and significant at the 1% level and falls between the OLS and SAR estimates at 2.12%. The estimated λ is positive and highly significant, also indicating the existence of spatial dependence.

Given that both the SAR and SEM models account for spatial correlation, how do we choose which model to use? A general spatial model that combines the two models by including

Table 2. Manufacturing as a Percentage of Private Wage and Salary Employment Regression Results for the OLS, SAR, and SEM Models

Independent Variable	OLS Estimates	SAR Estimates	SEM Estimates
Constant	−95.49 (−3.68)***	−31.35 (−1.82)*	−4.72 (−0.25)
Right-to-work dummy variable	3.02 (3.07)***	1.63 (2.49)**	2.12 (2.65)***
Small Business Survival Index	0.20 (2.83)***	0.09 (1.85)*	0.09 (1.49)
Population	0.00 (1.40)	0.00 (1.27)	0.00 (1.28)
Percentage of population aged 18–64	0.89 (4.99)***	0.27 (2.21)**	0.34 (2.42)**
Percentage of population age 25 or above with a bachelor's degree	−0.68 (−5.18)***	−0.27 (−3.14)***	−0.19 (−1.99)**
Percentage of population who are female	1.64 (5.14)***	0.52 (2.43)**	0.58 (2.62)***
Percentage of population who are Hispanic or Latino	−0.20 (−2.18)**	−0.04 (−0.67)	0.03 (0.40)
Percentage of population age 25 or above who are high school graduates or higher	−0.20 (−2.13)**	−0.07 (−1.04)	−0.33 (−3.53)***
Percentage of the population nonwhite	−0.13 (−2.42)**	−0.07 (−1.97)**	−0.11 (−2.30)**
Percentage of population that speaks language other than English at home	0.02 (0.14)	0.05 (0.58)	0.01 (0.06)
Persons per square mile	0.00 (1.12)	0.001 (0.62)	−0.001 (−0.62)
Mean travel time to work in minutes for persons age 16+	−0.07 (−0.70)	−0.02 (−0.30)	−0.05 (−0.55)
Rho		0.76 (21.46)***	
Lambda			0.84 (28.32)***
Adjusted R^2	0.3282	0.3672	0.7231
LM test—H_0: $\lambda=0$	324.34***	5380.24***	
Log-likelihood		−1269.8383	−1265.2561

t-statistics are in parentheses.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

both a spatially lagged dependent variable and a spatial error component could theoretically be utilized along with standard Lagrange multiplier (LM) diagnostic tests. Such a model is given by the following:

$$\begin{aligned} y &= \rho W_1 y + X\beta + u \\ u &= \lambda W_2 u + \varepsilon \\ \varepsilon &\sim N(0,\sigma^2 I_n) \end{aligned} \tag{3}$$

In this model, setting $\rho = \lambda = 0$ results in the familiar OLS specification. Allowing $\lambda = 0$ results in the SAR model, whereas setting $\rho = 0$ results in the SEM model. However, as noted in Anselin and Bera (1998, p. 252), the estimation of the general spatial model in Equation 3 can lead to identification issues in that the ρ and λ parameters cannot be separately identified. We avoid this problem by following the standard procedure in the spatial econometrics literature, which is to estimate the SAR and SEM models separately and utilize LM diagnostic tests to assist in model choice.[10] This methodology consists of first estimating the OLS specification and then testing for spatial error correlation using an LM test, where the null hypothesis H_0: λ

= 0 is tested against the alternative hypothesis H_a: $\lambda \neq 0$. Under the null hypothesis, the LM test statistic is distributed as χ^2 with one degree of freedom. If spatial error correlation is detected in the residuals, we first try to correct for this by employing the SAR model, as Anselin (1988, Chapter 8) notes that spatial error correlation may be due to a spatially correlated dependent variable. Using an LM test, we then test the residuals of the SAR model to determine if any spatial error correlation remains. Again, the null hypothesis H_0: $\lambda = 0$ is tested against the alternative hypothesis H_a: $\lambda \neq 0$. The LM test statistic is once again distributed as χ^2 with one degree of freedom under the null hypothesis. If there is still spatial error dependence, we estimate the SEM model. For the models estimated in Table 2, the LM test statistic is highly significant for the OLS specification, indicating that spatial error dependence is a concern. A similar conclusion is drawn from the LM test associated with the SAR model, in that spatial error dependence is still present even after including a spatially lagged dependent variable. Therefore, the SEM model would be the most appropriate model. Thus, we estimate the relationship between RTW legislation and manufacturing employment as a percentage of private wage and salary employment to be approximately 2.12%, the SEM estimate.

Table 3 shows the results of analyses based on alternative dependent variables. Given the sheer number of models estimated (168 in all), only the estimates of the RTW coefficients are presented, although the full set of results is available from the authors. The first three rows are based on alternatives to the manufacturing as a percentage of private wage and salary employment variable. The first of these is the absolute number of manufacturing employees in 2000. Such a variable was suggested by an anonymous reviewer because of the question of whether RTW laws actually influence the absolute level of employment or just the industrial mix of employment within a state. This variable is not significantly affected by RTW legislation in any of the three specifications. The next variable, however, is significantly related to RTW legislation in all specifications. It is manufacturing employment as a percentage of total employment. The preferred SEM estimate is 1.86 and is highly significant and smaller in magnitude than the OLS estimate. The third alternative manufacturing variable, the growth rate in manufacturing employment in 1947–1997, is not statistically related to RTW legislation in any specification. However, these results must be viewed cautiously, because demographic controls were unavailable for this specification.

The rest of the estimates in Table 3 are for measures of employment in other industries and for total employment. Given the results for manufacturing and the fact that none of the absolute employment variables is significantly related to RTW legislation, it is likely that rather than having an absolute effect on employment, RTW legislation affects only the industrial mix. In fact, if one adds up both the statistically significant and not statistically significant estimated coefficients on the RTW dummy for all the percentages of total specifications, the sum is zero. With respect to the other industry estimates there are several significant results. Agriculture, forestry, fishing and hunting, and mining employment as a percentage of total employment is negatively and marginally statistically significant in all specifications, a result that suggests that perhaps RTW laws are related to a movement away from agriculture, an industry that is not very unionized. However, this is a very broad census category that includes mining, a highly unionized industry that may be positively affected by RTW legislation, potentially masking a much larger negative effect on agriculture. Unfortunately we are limited by the broad census categories. On the other hand, information industry employment as a percentage of total employment is positive and statistically significantly related to the existence of an RTW law in

[10] For an example of a similar diagnostic methodology to the one outlined here, please see Garrett and Marsh (2002).

Table 3. Alternative Outcome Regressions: Estimated Right to Work Coefficients[a]

Outcome[b]	OLS Estimate	SAR Estimate	SEM Estimate
Manufacturing employment	315.15 (1.07)	329.83 (1.14)	329.71 (1.06)
Manufacturing employment as a percentage of total employment	2.58 (3.39)***	1.48 (2.94)***	1.86 (3.02)***
Growth rate in manufacturing employment 1947–1997[b]	1168.91 (1.36)	1177.60 (1.38)	1207.95 (1.40)
Agriculture, forestry, fishing and hunting, and mining employment	−99.27 (−1.33)	−83.25 (−1.17)	−101.40 (−1.29)
Agriculture, forestry, fishing and hunting, and mining employment as a percentage of total employment	−1.30 (−1.77)*	−1.16 (−1.95)*	−1.26 (−1.77)*
Construction employment	29.79 (0.24)	35.77 (0.29)	−29.18 (−0.31)
Construction employment as a percentage of total employment	−0.26 (−1.31)	−0.18 (−1.00)	−0.04 (−0.20)
Wholesale trade employment	8.54 (0.13)	12.43 (0.19)	8.54 (0.12)
Wholesale trade employment as percentage of total employment	0.11 (1.00)	0.10 (0.99)	0.11 (0.93)
Retail trade employment	131.43 (1.47)	130.33 (1.48)	138.53 (1.51)
Retail trade employment as a percentage of total employment	0.07 (0.31)	0.06 (0.29)	0.04 (0.18)
Transportation and warehousing employment and utilities employment	67.98 (0.83)	69.67 (0.87)	49.42 (0.68)
Transportation and warehousing employment and utilities employment as a percentage of total employment	0.04 (0.23)	0.02 (0.12)	0.03 (0.16)
Information employment	99.00 (0.69)	104.47 (0.74)	78.75 (0.51)
Information employment as a percentage of total employment	0.22 (2.68)***	0.19 (2.55)**	0.20 (2.37)**
Finance, insurance, real estate, and rental and leasing employment	−34.87 (−0.26)	−38.91 (−0.29)	−43.69 (−0.32)
Finance, insurance, real estate, and rental and leasing employment as a percentage of total employment	−0.12 (−0.85)	−0.10 (−0.77)	−0.17 (−1.20)
Professional, scientific, management, administrative, and waste management services employment	71.65 (0.18)	89.44 (0.24)	14.73 (0.04)
Professional, scientific, management, administrative, and waste management services employment as a percentage of total employment	0.28 (1.96)*	0.27 (2.07)**	0.25 (1.70)*
Educational, health, and social services employment	−315.11 (−1.29)	−358.87 (1.50)	−316.35 (−1.38)
Educational, health, and social services employment as a percentage of total employment	−0.58 (−1.34)	−0.32 (−0.82)	−0.26 (−0.59)
Arts, entertainment, recreation, accommodation, and food services employment	324.72 (0.49)	267.34 (0.41)	273.89 (0.52)

Table 3. Continued

Outcome[b]	OLS Estimate	SAR Estimate	SEM Estimate
Arts, entertainment, recreation, accommodation, and food services employment as a percentage of total employment	−0.69 (−1.92)*	−0.44 (−1.41)	−0.54 (−1.47)
Other services (except public administration) employment	−86.84 (−0.96)	−88.11 (−0.99)	−101.47 (−1.07)
Other services (except public administration) employment as a percentage of total employment	−0.23 (−2.26)**	−0.21 (−2.17)**	−0.23 (−2.19)**
Public administration employment	−10.79 (−0.04)	17.50 (0.06)	−50.75 (−0.16)
Public administration employment as a percentage of total employment	−0.12 (−0.50)	−0.09 (−0.41)	−0.10 (−0.40)
Total employment	501.39 (0.57)	427.26 (0.49)	500.13 (0.57)

t-statistics are in parentheses.
[a] The full set of regression coefficients is available from the authors upon request.
[b] All data are for 2000 except for growth rate in manufacturing employment 1947–1997.
[c] Based on 194 observations because of missing values. No demographic variables are included for this specification because of a lack of data.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

all specifications, suggesting that this industry may also benefit from RTW laws, although the coefficient estimate is small, only 0.2% in the SEM model. Similarly, employment in the professional, scientific, management, administrative and waste management services industry as a percentage of total employment is also positively and significantly affected by the existence of an RTW law. This makes sense given that some types of workers in this broad category are highly unionized. However, because the category is so broad and also includes several types of workers with low unionization rates, this may explain the small coefficient estimate on the RTW variable of 0.25 in the SEM model. Finally, employment in the other services (except public administration) industries as a percentage of total employment is negatively associated with RTW legislation, a result suggesting that RTW legislation may steer local employment away from services and towards manufacturing, although the effect is small, −0.23% in the SEM model. A result that is surprising, however, is that no relationship between RTW legislation and employment is found in other heavily unionized industries such as construction, transportation and warehousing, and utilities. However, such insignificant results may help explain why the literature has primarily focused on manufacturing.

Table 4 shows the results from LM tests to ascertain whether or not spatial dependence exists in the errors of the OLS and SAR specifications for the alternative outcome models. The vast majority of the models tested reject the null hypothesis H_0: $\lambda = 0$ against the alternative hypothesis H_a: $\lambda \neq 0$ for both the OLS and SAR specifications, thereby justifying the use of the SEM model for purposes of inference.

6. Conclusion

RTW laws are thought to decrease the power of unions and thus to attract manufacturing employment to a state. Previous evidence on the effectiveness of these laws is mixed, although

Table 4. Specification Tests for Spatial Autocorrelation in Alternative Outcome Regressions[a]

Outcome[b]	LM Test Statistic for OLS Models (H_0: $\lambda=0$)	LM Test Statistic for SAR Models (H_0: $\lambda=0$)
Manufacturing employment	9.34***	18.56***
Manufacturing employment as a percentage of total employment	327.81***	5128.74***
Growth rate in manufacturing employment 1947–1997[c]	0.09	26.54***
Agriculture, forestry, fishing and hunting, and mining employment	20.27***	101.14***
Agriculture, forestry, fishing and hunting, and mining employment as a percentage of total employment	171.52***	1531.74***
Construction employment	22.64***	27.35***
Construction employment as a percentage of total employment	69.44***	450.43***
Wholesale trade employment	8.44***	11.63***
Wholesale trade employment as a percentage of total employment	10.41***	230.27***
Retail trade employment	3.84**	3.90**
Retail trade employment as a percentage of total employment	19.91***	297.74
Transportation and warehousing employment and utilities employment	8.10***	8.60***
Transportation and warehousing employment and utilities employment as a percentage of total employment	44.49***	676.14***
Information employment	1.11	6.90***
Information employment as a percentage of total employment	13.18***	47.07***
Finance, insurance, real estate, and rental and leasing employment	1.64	1.58
Finance, insurance, real estate, and rental and leasing employment as a percentage of total employment	44.48***	272.77***
Professional, scientific, management, administrative, and waste management services employment	0.11	2.14
Professional, scientific, management, administrative, and waste management services employment as a percentage of total employment	15.67***	23.17***
Educational, health, and social services employment	0.99	4.81**
Educational, health, and social services employment as a percentage of total employment	77.62***	778.29***
Arts, entertainment, recreation, accommodation and food services employment	13.71***	27.08***
Arts, entertainment, recreation, accommodation and food services employment as a percentage of total employment	93.00***	870.03***
Other services (except public administration) employment	0.02	0.08
Other services (except public administration) employment as a percentage of total employment	6.31**	96.30***
Public administration employment	0.94	14.12***
Public administration employment as a percentage of total employment	74.95***	611.14***
Total employment	0.01	0.04

[a] The LM test statistic is distributed chi-square with one degree of freedom under the null hypothesis.
[b] All data are for 2000 except for growth rate in manufacturing employment 1947–1997.
[c] Based on 194 observations because of missing values. No demographic variables are included because of a lack of data.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

many recent studies suggest that RTW laws do positively affect employment. However, many of these studies suffer from omitted variable bias because of unmeasurable geographic characteristics such as public attitudes or natural or labor resources. In addition, failure to correct for spatial autocorrelation can result in coefficient estimates that are both biased and inconsistent. Our estimates that do not account for geographically correlated omitted factors dramatically overstate the positive relationship between RTW legislation and manufacturing employment. When we do control for geographically correlated omitted factors, we estimate that RTW legislation is associated with an increase in manufacturing's share of private wage and salary employment of 2.12%, an estimate almost 30% lower than the estimate that does not control for these spatially correlated omitted factors. Results for other industries indicate that right to work legislation is negatively associated with employment shares in the agriculture, forestry, fishing and hunting, and mining industries and in some service industries but positively associated with employment shares in the information and professional, scientific, management, administrative, and waste management services industries. Improperly controlling for geographic factors can lead to incorrect inferences and misinform policy.

Appendix: Data Sources 10

Variable Description	Source
2000 manufacturing employment as a percentage of total private wage and salary employment	2000 Decennial Census Summary File 4 Sample Data: Profile of Selected Economic Characteristics. U.S. Bureau of the Census.
Growth rate in manufacturing employment 1947–1997	City and County Data Books. http://fisher.lib.virginia.edu/collections/stats/ccdb.
2000 percentage of population aged 18–64	Computed using total population and populations under 18 and 65 and older. State and County Quick Facts. U.S. Bureau of the Census. http://quickfacts.census.gov/qfd/.
2000 percentage of population that is female	http://quickfacts.census.gov/qfd/.
2000 percentage of population that is Hispanic or Latino	http://quickfacts.census.gov/qfd/.
2000 percentage of population that is nonwhite	Subtracted percentage white from 100. http://quickfacts.census.gov/qfd/.
2000 percentage of population aged 25 or above with at least a high school degree	http://quickfacts.census.gov/qfd/.
2000 percentage of population aged 25 or above with a bachelor's degree	http://quickfacts.census.gov/qfd/.
2000 percentage of population that speaks a language other than English at home	http://quickfacts.census.gov/qfd/.
2000 persons per square mile	http://quickfacts.census.gov/qfd/.
2000 mean travel time to work in minutes for persons aged 16 +	http://quickfacts.census.gov/qfd/.
2000 Small Business Survival Index	Small Business and Entrepreneurship Council. http://www.sbsc.org/index.asp.
2000 right-to-work dummy variable	Right-to-work status was determined by checking 1998–2003 issues of the *Monthly Labor Review* published by the Bureau of Labor Statistics, http://www.bls.gov/opub/mlr/archive.htm

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