J Labor Res (2008) 29:303–317
DOI 10.1007/s12122-007-9038-6

Effects of Minimum Wages on Youth Employment: the Importance of Accounting for Spatial Correlation

Charlene M. Kalenkoski · Donald J. Lacombe

Published online: 9 September 2007

Abstract The relationship between minimum wage increases and youth employment is investigated using county-level data and spatial econometric techniques. Results that account for spatial correlation indicate that a 10% increase in the effective minimum wage is associated with a 3.2% decrease in youth employment, a result that is 28% higher than the corresponding estimate that does not control for spatial correlation. Thus, estimates that do not take into account spatial correlation may significantly underestimate the negative effect of the minimum wage on teenage employment. Improperly controlling for factors that vary systematically over space can lead to incorrect inferences and misinform policy.

Keywords Spatial econometrics · Spatial autoregressive model · Minimum wage · Youth employment

Introduction

The literature analyzing the effects of minimum wages in the United States is quite large. There have been case studies of particular state minimum wage changes, time series studies of the effects of federal minimum wage changes, and cross-sectional and panel studies that investigate "effective" minimum wages, the maximum of state and federal minimums. They have often focused on teenage or youth employment as young, unskilled individuals are those thought most likely to

C. M. Kalenkoski (✉)
Department of Economics, Ohio University, 351 Bentley Annex, Athens, OH 45701, USA
e-mail: kalenkos@ohio.edu

D. J. Lacombe
Department of Economics, Ohio University, 345 Bentley Annex, Athens, OH 45701, USA

be affected by minimum wages. Elasticities of employment with respect to minimum wage changes have been estimated to be negative, positive, and not statistically different from zero [1].

One reason for such varying results is differences in how studies account for unobserved variables that are thought to affect employment such as policy climate and overall economic and labor market conditions. Most studies include state-level proxies for these variables. Some studies also use control groups to account for unobserved factors. Panel studies often include state and year fixed effects. However, it is unlikely that these techniques account for all relevant unobserved factors and some of these factors may be correlated across geographic boundaries. Yet almost no studies have attempted to account for such spatial correlation.

This study attempts to remedy this deficiency in the literature by estimating the effects of minimum wages on teenage employment using cross-sectional analysis, county-level data, and relatively new spatial econometric techniques to account for spatial autocorrelation.

Literature Review

Most of the minimum wage literature has acknowledged the need to control for unobserved geographic factors that may be correlated with the minimum wage and employment yet the methods for doing this and the resulting estimates have been varied. A very early time series study of the effects of minimum wages on employment (Lianos 1972) analyzed the effect of the federal minimum wage on farm labor and found that the minimum wage increased farm wages and decreased farm employment as expected. To minimize the bias due to unobserved geographic factors, this study focused on the south and used regional wage measures to account for geographic differences.

A much more recent time series study by Card (1992a) examined the effect of the April 1990 rise in the federal minimum wage on teenage wages and employment. In order to control for omitted geographic factors, Card grouped states into three categories based on whether or not they had low, medium, or high fractions of affected workers in 1989 and found, using quarterly data, that while teenage wages increased, teenage employment was unaffected.

In another study, Card (1992b) investigated the effects of a 1988 California state minimum wage increase via a differences-in-differences approach. In this paper he compared changes in wages and employment of California workers to changes in wages and employment of workers in a group of states with no increase in the minimum wage. These control group states included Arizona, Florida, Georgia, New Mexico, and Texas. Card stated that a control group of neighboring states would have been preferred but that other neighboring states also had minimum wage increases and so could not be used. Using Current Population Survey (CPS) and other data he found that, consistent with his other results, the earnings of low-wage workers were increased by 5–10% but that there was no decline in employment. In fact, Card

[1] A recent review of the literature by Neumark and Wascher (2006) shows that the weight of the evidence supports a negative effect of minimum wages on employment.

suggested that the minimum wage increase caused an *increase* in the teenage employment–population ratio, and that a monopsony model may be a more appropriate model of the teenage labor market than the competitive model. Contradictory to these findings, however, Card also found that employment growth was weaker in California than in the control group states and the country as a whole, a result suggestive of a negative effect of the increased minimum wage. While Card dismissed this implication by attributing the difference in employment growth to long run trends, his explanation suggests a potential problem with the control group used.

Card and Kreuger (1994) also took a control group approach in investigating the effects of a 1992 increase in New Jersey's minimum wage. They compared employment growth at fast food restaurants in New Jersey that were subject to the minimum wage increase to employment growth at fast food restaurants in eastern Pennsylvania, a neighboring state, that were not subject to a minimum wage increase. Like all studies that use the control group technique, there is concern about control group composition as restaurants that were being compared were not necessarily located in neighboring counties. For example, restaurants on the Jersey Shore were compared to restaurants in eastern Pennsylvania. The authors also compared employment changes at stores in New Jersey that were initially paying high wages (above the new minimum) to changes at lower wage stores (below the new minimum). However, there may have been inherent differences between these two types of stores that would render the control group invalid. Card and Kreuger found that employment did not decrease in response to an increase in the minimum wage when either of these comparisons was used. Rather, employment increased in stores affected by the minimum wage. When regional dummies were added, however, in some instances the minimum wage variable was statistically insignificant rather than significantly positive, suggesting the importance of omitted geographic factors.

Neumark and Wascher (2000) replicated Card and Kreuger's (1994) study using payroll data and found an opposite result to that of Card and Krueger, that the increase in New Jersey's minimum wage decreased employment in the fast-food industry. They attributed their different finding to the different data that they used. Card and Krueger (2000) responded with an analysis using administrative data that confirmed their original result, that the New Jersey minimum wage increase probably had no effect on employment in New Jersey's fast food industry but possibly had a small positive effect. Michl (2000) reconciled these apparently contradictory results by attributing them to "rescheduling" by employers. Employers did not reduce the number of workers in response to a minimum wage increase. Rather, they reduced hours worked per worker, consistent with a decline in the quantity of labor demanded by employers as a result of an increase in the cost of labor.

Cross-sectional studies have also been performed to investigate the effects of effective minimum wages. For example, Card (1992a) investigated the change in teenage employment across states before and after the 1990 federal minimum wage increase. In this case, he controlled for omitted geographic factors by including on the right hand side of his regression the change in the overall employment–population rate and the change in the overall unemployment rate. He found that while teenage wages increased, teenage employment was unaffected.

Wessels (1993) used cross-sectional data to analyze the effects of minimum wages on tipped employees, controlling for geography by including region dummies and state-level variables measuring economic conditions in his regressions. His results suggested that a 10% increase in the minimum wage would decrease the employment of tipped workers by 4%, reduce the number of hours worked by 6%, and reduce the total income of all restaurant servers, whether tipped or not, by 3–5%.

Schiller (1994) performed a cross-sectional analysis on 1980–1981 data from the National Longitudinal Survey of Youth (NLSY). He regressed a state's youth employment rate on the state's adult employment rate, the state's average manufacturing wage, the state's adult unemployment rate, region dummies, a measure of the minimum wage, and a variable indicating minimum wage coverage provisions. He found that the level of a state's minimum wage had little impact on youth employment or entry wages, although coverage provisions indicating who was covered by a minimum wage do appear to have had an effect.

One of the problems with cross-sectional studies, however, is that when an observation is a state, unobserved economic conditions and policy climate cannot be captured by including state indicator variables as explanatory variables. In response to this concern, several studies have used panel data, which allow use of state and year fixed effects, to investigate the effects of minimum wages. For example, Neumark and Wascher (1992) used panel data for 1973–1989 to investigate the employment effects of minimum wages on teenagers, including state as well as year fixed effects to control for unobserved factors. They found that a 10% increase in the minimum wage led to a decline in the employment of teenagers of 1–2% and a decline in the employment of adults by 1.5–2%.

Williams (1993) also used panel data for 1977–1989 to investigate regional variation in the effects of minimum wages on the employment of teenagers. He controlled for geographic factors by including region dummies and region dummies interacted with his minimum wage variable and found that there were negative effects of minimum wages on the employment of teenagers and that these effects varied by region. In some regions there was almost a 7% reduction in teenage employment. While Williams did not utilize a state fixed-effects estimator, he did note that one would be desired if there were unobserved differences across states that were important in determining teenage employment. He did not utilize such an estimator because his sample size did not allow a fixed effects estimator that accommodates differing slope coefficients.

Neumark and Wascher (1995) estimated a conditional logit model of employment and school enrollment outcomes for teenagers using panel data on fifty states and the District of Columbia for the period 1977–1989. Their results showed a positive effect of minimum wages on the proportion of teens neither employed nor in school and suggested that employers substitute higher- for lower-skilled teenagers, leaving displaced teenagers both out of work and out of school as a result. They controlled for geography by including measures of the prime-age male unemployment rate and the proportion of the population aged 16–19 as well as state fixed effects.

Partridge and Partridge (1998) used panel data from the late 1980s to examine the effects of effective minimum wages on teenage unemployment rates. To control for geographic differences in labor market conditions they included the natural log of the share of the state's non-supervisory labor force covered by the federal minimum wage, the natural log of the average hourly manufacturing production worker wage, a measure of state employment growth, age group dummies to indicate the supplies of workers of different ages in different states in different years, and state and year fixed effects. Their results indicated that the overall effect of an increase in the minimum wage was to increase unemployment. In a subsequent analysis, Partridge and Partridge (1999) examined the effects of effective minimum wages on employment in the retail sector, a relatively low-wage sector. These results suggested that an increased minimum wage reduces retail employment consistent with the standard labor market model.

Finally, Zavodny (2000) examined the effect of minimum wage increases on teen hours of work and employment using both state- and individual-level data from the CPS Outgoing Rotation groups for the period 1979–1993. She included the unemployment rate of males aged 25–64, the ratio of teens aged 16–19 to the total population aged 16–64, and state and year fixed effects to control for unobserved economic conditions. She found that while minimum wages did not significantly reduce teenage hours of work, they may have had a small negative effect on teenage employment.

All of the aforementioned studies attempted to control for omitted geographic factors. However, the possibility exists that when proxy variables or state fixed effects are used, there are remaining unobserved factors that affect both the minimum wage and employment and are spatially correlated, leading to biased and inefficient estimates. Previous work with respect to the effect of right-to-work legislation on manufacturing employment suggests that estimated policy effects may indeed be biased when spatial correlation is not taken into account (Kalenkoski and Lacombe 2006). Therefore this study attempts to control for spatial correlation in estimating the effect of minimum wages on teenage employment by using not only proxies to help control for omitted geographic factors, but also spatial econometric techniques.

Data Description and Variables

The dependent variable of interest in this paper is the natural log of the ratio of the employment of 16–19 year olds in a county to the population of 16–19 year olds in the county[2]. The data used to construct this variable were taken from the 2000 Decennial Census Summary File 3 and are made available online by the U.S. Bureau of the Census[3]. Data on 3,065 counties were used, excluding those in Alaska and Hawaii given that counties in those states do not border other states[4]. The key explanatory variable of interest is the natural log of the effective minimum wage in 2000. This variable was constructed by taking the maximum of the federal and state minimum wages in a state, using the federal rate where no state minimum wage

[2] The analysis is a cross-sectional rather than a panel one due to limitations in the availability of data at the county level as well as changing county definitions over time.

[3] http://factfinder.census.gov/home/saff/main.html? _lang=en.

[4] Washington, D.C. and cities in Virginia, which technically do not reside in counties, were also excluded.

existed. Data on state and federal minimum wages can be found on the U.S. Bureau of Labor Statistics (BLS) website[5].

Several other explanatory variables were also constructed using Census and BLS data. The natural log of county-level per capita income and the adult (age 25–64) male unemployment rate were constructed from the same Census data as the dependent variable and are included in the analysis to proxy for general economic conditions. These county-level variables were chosen to be similar to the state-level variables used in other minimum wage studies. Per capita income was included by Wessels (1993) to control for product demand. Card (1992a) and Schiller (1994) included the overall unemployment rate and the adult unemployment rate respectively to control for labor market conditions. The more recent panel studies of Neumark and Wascher (1995) and Zavodny (2000) have used the state-level adult male unemployment rate. Also constructed from Census data are several proxies for labor supply characteristics that include the natural log of the percent of the population that is white and the natural logs of the percents of the population over 25 that have less than a high school degree, a high school degree, a college degree, and a graduate degree as their highest level of educational attainment. While labor force characteristics such as these have been ignored by other cross-sectional studies, they are included here as important determinants of employment. The percent of the population that is rural is also included as a proxy for both supply and demand characteristics[6]. This control is similar in spirit to Wessels' (1993) percent of a state's population living in a metropolitan area variable. Finally, from BLS data, the natural log of the county average wage in 2000 is also included[7,8]. While both Wessels (1993) and Schiller (1994) include the state average manufacturing wage in their analyses and Wessels (1993) also includes the average weekly retail wage in his analysis, the county average wage over all industries has been used in this study for two reasons. First, manufacturing has declined in importance in the U.S. economy. Second, industry-level wages are not available at the county level. Descriptive statistics for all of the variables used in the analysis are shown in Table 1.

Econometric Model

As noted earlier, many studies of the effect of minimum wages on various measures of employment have tried to proxy for unobserved geographic factors that may vary systematically over space. This phenomenon is referred to as spatial autocorrelation and is formally defined as follows (Anselin and Bera 1998):

$$\text{cov}\left(y_i, y_j\right) = E\left(y_i, y_j\right) - E(y_i)E\left(y_j\right) \neq 0 \;\; for\, i \neq j \tag{1}$$

[5] http://www.dol.gov/esa/programs/whd/state/MWHistoryTable.pdf.

[6] The county-level adult male unemployment rate and the percent rural are not logged because a small number of zero values were reported for each.

[7] http://www.bls.gov/cew/home.htm.

[8] For a very small number of counties that were missing a value for the average county wage, the missing value was replaced with the average over all counties in the state and a missing value dummy variable was created and included in all specifications.

Table 1 Descriptive statistics

Variable name	Mean	SD	Min	Max
Minimum wage	5.21	0.24	5.15	6.50
Per capita income	17,454.41	3,894.57	5,213	44,962
Average weekly wage	479.91	108.76	199	1,466
Adult male unemployment rate	4.26	2.47	0	30.69
Percent white	84.98	15.86	5.01	100
Percent less than high school degree	22.66	8.74	3.04	65.30
Percent with high school degree	34.81	6.51	10.93	53.25
Percent with college degree	16.61	5.97	4.88	45.25
Percent with graduate degree	5.49	3.19	0.90	36.03
Percent rural	60.67	30.37	0	100
Number of Observations	3,065			

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 and this spatial autocorrelation requires the use of spatial econometric techniques.

A family of related spatial econometric models can be represented by the following:

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

where $\mathbf{y}$ represents an $n{\times}1$ dependent variable vector, ρ is the scalar spatial dependence parameter, $\mathbf{W}$ is an $n \times n$ spatial weights matrix, $\mathbf{X}$ denotes the $n \times k$ vector of independent variables, and $\boldsymbol{\beta}$ is an $n \times 1$ vector of associated regression parameters. The error vector $\boldsymbol{\varepsilon}$ is modeled to follow a spatial autoregressive process with dependence parameter λ, and $\boldsymbol{\varepsilon}$ is an $n \times 1$ vector of normally distributed stochastic disturbances.

The general model in Eq. 2, which is known as the spatial autocorrelation (SAC) model, includes spatial dependence in both the dependent variable $\mathbf{y}$ as well as the error term $\boldsymbol{\varepsilon}$. Special cases of this general model can be obtained by restricting parameters. For example, setting the parameter λ=0, we obtain a model that exhibits spatial dependence only in the dependent variable $\mathbf{y}$. This model is the spatial autoregressive (SAR) model. The spatial error model (SEM) arises from restricting the parameter ρ=0, resulting in spatial dependence in the error term alone. Placing the restrictions λ=0 and ρ=0, which indicates the lack of any spatial autocorrelation, results in the familiar ordinary least squares (OLS) specification.

The $\mathbf{W}$ term in the above equation represents a first-order spatial contiguity matrix, "which expresses for each observation (row) those locations (columns) that belong to its neighborhood set as nonzero elements" (Anselin and Bera 1998). Suppose that there are four counties with county #1 being a neighbor to county #2 and #3, county #2 being a neighbor to counties #1 and #3, and county #4 being a neighbor to only county #3. The first order contiguity matrix shown below as Eq. 3

is a convenient way in which to represent the spatial configuration of a sample of counties:

$$\mathbf{W}=\begin{pmatrix}0&1&1&0\\1&0&1&0\\1&1&0&1\\0&0&1&0\end{pmatrix} \tag{3}$$

The matrix in Eq. 3 has elements equal to 1 if two counties share a common border (i.e. are first order contiguous) and a 0 if they do not share a border. For example, county #1 shares a common border with counties #2 and #3 so in row 1 of the matrix a one is entered into the spatial weight matrix in columns 2 and 3 to represent the contiguity between these counties. Similarly, we code the second row of the spatial weight matrix with a one on columns 1 and 3 to represent the fact that county #2 shares a border with counties #1 and #3. In turn, each row illustrates the contiguity relationship for each of the four counties. Note that, by definition, the main diagonal of the spatial weight matrix contains zeros because a county cannot be a neighbor to itself.

Normally, a row stochastic weight matrix is used in a regression modeling context, which means that the rows of the spatial weight matrix sum to unity. Converting the spatial weight matrix in Eq. 3 above to a row stochastic spatial weight matrix yields the following converted weight matrix:

$$\mathbf{W}=\begin{pmatrix}0&.5&.5&0\\.5&0&.5&0\\.3&.3&0&.3\\0&0&1&0\end{pmatrix} \tag{4}$$

This transformation of the spatial weight matrix provides for an intuitive explanation for the **Wy** and **Wu** terms. The **Wy** term can be thought of as a weighted average of the surrounding observations on the dependent variable, and **Wu** can be thought of as a weighted average of the surrounding error terms. Depending on the regression modeling context, both ρ and λ measure the extent of the spatial autocorrelation.

Given the spatial econometric models outlined above, it is instructive to illustrate when the SAR and SEM models would be utilized. The SAR model is used when one believes that the spatial dependence is inherent in the dependent variable. Spatial dependence in the dependent variable may arise due to several factors. First, there may be agglomeration economies, whereby firms locate next to each other for cost savings or to take advantage of natural resources, such as convenient shipping routes offered by lakes and rivers. Second, in terms of labor markets, there may be "employment centers" that draw employees from several surrounding counties. Third, 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.[9]

[9] Anselin (1988) provides an example of measurement error.

The SAR model results from placing the restriction λ=0 on Eq. 2 and is given by the following:

$$\begin{array}{c} \mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \\ \boldsymbol{\varepsilon} \sim N(\mathbf{0}, \sigma^2\mathbf{I_n}) \end{array} \tag{5}$$

It is important to note that the inclusion of the **Wy** term on the right hand side of Eq. 5 introduces simultaneity bias and therefore the use of OLS as an estimation strategy will produce biased and inconsistent parameter estimates (Anselin 1988). Therefore maximum likelihood estimation is used to estimate the parameters in the SAR model. Lee (2004) has shown that the maximum likelihood method for SAR models has the usual desirable asymptotic properties [10]. The log likelihood for the model expressed in Eq. 5 above under the assumption of normally distributed error terms, $\boldsymbol{\varepsilon}$, and homoskedasticity is given by (Anselin 2001):

$$\begin{array}{c} \ln L = -\left(\frac{n}{2}\right)\ln(2\pi) - \left(\frac{n}{2}\right)\ln\sigma^2 \\ + \ln|\mathbf{I_n} - \rho\mathbf{W}| - \left(\frac{1}{2\sigma^2}\right)(\mathbf{y} - \rho\mathbf{W}\mathbf{y} - \mathbf{X}\boldsymbol{\beta})'(\mathbf{y} - \rho\mathbf{W}\mathbf{y} - \mathbf{X}\boldsymbol{\beta}) \end{array} \tag{6}$$

The key coefficients of interest are ρ and the coefficient on the minimum wage variable as we are interested in whether or not spatial dependence exists and the relationship between minimum wage laws and youth employment. In particular, if ρ is statistically significantly different from zero there is spatial dependence in the dependent variable, suggesting that agglomeration economies, employment centers, or measurement error in the dependent variable exists. If the minimum wage coefficient is greater than zero, then minimum wage laws are positively associated with youth employment. Alternatively, if the minimum wage coefficient is less than zero, minimum wage laws are negatively associated with employment.

A second type of spatial dependence involves spatial correlation across the error terms. It is possible that when an econometric model is specified and estimated, there may be variables that are omitted that are spatially related to each other over space. The conditions under which spatial residual autocorrelation arise is nicely illustrated in a housing context by Dubin (1998): “Housing prices are a prime example: clearly the location of the house will have an effect on its selling price. If the location of the house influences its price, then the possibility arises that nearby houses will be affected by the same location factors. Any error in measuring these factors will cause their error terms to be correlated.”As also noted by Dubin (1998), “The consequences of spatial autocorrelation are the same as those of time series autocorrelation: the OLS estimators are unbiased but inefficient, and the estimates of the variance of the estimators are biased." It should be noted that the OLS estimators will remain unbiased if the omitted variable that is geographically correlated is uncorrelated with the remaining explanatory variables.

[10] Given maximum likelihood estimation’s dependence on the assumption of normality, we also estimated our models using the Generalized Method of Moments (GMM) technique and found that our results were not sensitive to the method used.

The SEM model results from placing the restriction ρ=0 on Eq. 2 and results in the following:

$$\begin{aligned} \mathbf{y} &= \mathbf{X}\boldsymbol{\beta} + \mathbf{u} \\ \mathbf{u} &= \lambda\mathbf{W}\mathbf{u} + \boldsymbol{\varepsilon} \\ \boldsymbol{\varepsilon} &\sim N\left(\mathbf{0}, \sigma^2\mathbf{I_n}\right) \end{aligned} \tag{7}$$

Like the model with spatial dependence in the dependent variable, estimation of this model via OLS results in parameter estimates that are unbiased but inefficient so maximum likelihood techniques are used. Anselin (2001) provides the following log likelihood function under the assumption of normally distributed error terms, $\boldsymbol{\varepsilon}$, and homoskedasticity used in estimating the SEM model:

$$\begin{gathered} \ln L = -\left(\tfrac{n}{2}\right)\ln(2\pi) - \left(\tfrac{n}{2}\right)\ln\sigma^2 \\ + \ln|\mathbf{I_n} - \lambda\mathbf{W}| - \left(\tfrac{1}{2\sigma^2}\right)(\mathbf{y} - \mathbf{X}\boldsymbol{\beta})'(\mathbf{I_n} - \lambda\mathbf{W})'(\mathbf{I_n} - \lambda\mathbf{W})(\mathbf{y} - \mathbf{X}\boldsymbol{\beta}) \end{gathered} \tag{8}$$

The $\lambda\mathbf{Wu}$ term in Eq. 7 above uses the same row stochastic spatial weight matrix $\mathbf{W}$ used in the first model but now it defines the contiguity relationship amongst the error terms.

Given the fact that there are three spatial econometric models that potentially could be utilized, the SAC, SAR, and SEM models, we now turn our focus to the topic of model choice. Because the SAC model does not provide for separate identification of the ρ and λ parameters when estimated via maximum likelihood, we do not estimate this model as our preferred specification[11]. However, we do estimate it as a sensitivity analysis using a generalized method of moments (GMM) estimator developed by Kelejian and Prucha (1998).

Anselin et al. (1996) provide several Lagrange Multiplier (LM) tests to assist in choosing between the SAR and SEM models. These Lagrange Multiplier tests fall into two basic categories: non-robust and robust. The non-robust test statistics are used to test the residuals of an OLS regression model for the presence of either a spatially lagged dependent variable (the LM Lag test) or for the presence of a spatially autocorrelated error term (the LM Error test). Both of these test statistics are distributed as χ^2 with one degree of freedom under the null hypothesis. The other two Lagrange Multiplier test statistics are of the robust variety. The LM Lag Robust statistic tests the residuals of an OLS regression model for a spatially lagged dependent variable when the specification potentially contains a spatially autocorrelated error term, i.e. it tests whether there is a spatially lagged dependent variable when there is spatial error autocorrelation. The LM Error Robust statistic tests the residuals of an OLS regression for the presence of spatial error autocorrelation when the specification potentially contains a spatially lagged dependent variable. In this case, the test is for the presence of spatial error autocorrelation when there is a spatially lagged dependent variable. The robust test statistics are also distributed as χ^2 with one degree of freedom under the null hypothesis.

[11] Please see Anselin and Bera (1998).

Florax et al. (2003) outline a procedure for using these test statistics to determine which model is the more appropriate one[12]. The first step involves calculation of both the LM Lag and LM Error test statistics, the results of which appear in Table 2. Our results indicate that both the LM Lag and LM Error test statistics are highly statistically significant. According to the procedure outlined in Florax et al. (2003), when both non-robust test statistics are highly significant, the next step involves calculating the robust varieties of these tests. When both of these are statistically significant, the researcher should choose the one with higher test statistic. Our results in Table 2 indicate that both robust test statistics are statistically significant but that the LM Lag Robust test statistic is higher. Therefore, we use the SAR model in our analysis. Our results from the GMM SAC model, as indicated in Table 3, also show that the SAR model is the preferred model because the spatial error term λ is statistically insignificant. However, estimates of the effect of the minimum wage on the teenage employment rate are quite similar across the SAC, SAR, and SEM models.

Results

Table 2 shows the OLS regression estimates. The key result, the coefficient on the effective minimum wage variable, indicates that a 10% increase in the effective minimum wage leads to a statistically significant decrease in the youth employment/ population ratio of 2.5%, a result within the range of estimates found in the literature. Our three measures of general economic conditions, per capita income, the average weekly wage, and the adult male unemployment rate, are also statistically significant. Per capita income is positively related to youth employment, and the average weekly wage and the adult male unemployment rate are negatively related to youth employment. While the signs on the per capita income and unemployment rate coefficients are as expected, indicating that teen employment is increased in good economic times and decreased in poor economic times, the negative coefficient on the average weekly wage was unexpected. Perhaps rather than proxying for general economic conditions this variable is measuring parents' wages and a teens' need to work. Teens with higher earning parents may be less likely to seek work than teens with lower-earning parents.

All of the labor supply characteristics except the percent of the population without a high school degree are statistically significant. As expected, the percents of the population that are white, high school graduates, and college graduates are positively related to teen employment. However, the percent of the population with a graduate degree is negatively associated with teen employment. Perhaps this reflects teens with highly educated parents being less likely to seek employment. Finally, the percent rural is also negatively associated with teen employment and may be measuring a lack of teen employment opportunities in rural areas.

[12] Anselin et al. (1996) provide Monte Carlo evidence that the Lagrange Multiplier tests utilized in this study may be superior to Wald and Likelihood Ratio tests for spatial dependence.

Table 2 OLS regression estimates

Explanatory variables	Estimated coefficient	t Statistic
Constant	−7.77	−20.03***
ln(minimum wage)	−0.25	−2.55**
ln(per capita income)	0.55	14.63***
ln(average weekly wage)	−0.19	−6.65***
Adult male unemployment rate	−0.02	−11.46***
ln(percent white)	0.35	17.58***
ln(percent with less than high school degree)	−0.02	−0.72
ln(percent with high school degree)	0.4	13.34***
ln(percent with college degree)	0.18	6.88***
ln(percent with graduate degree)	−0.08	−5.54***
Percent rural	−0.002	−12.84***
Number of observations	3,065	
Adjusted R squared	0.54	
LM lag	896.30***	
LM error	797.61***	
LM lag robust	177.92***	
LM error robust	79.23***	

Dependent variable: log of youth employment to population ratio
*Significant at the 10% level
**Significant at the 5% level
***Significant at the 1% level

The results from the SAR model are shown in Table 4. It should be noted that each estimated coefficient in the SAR model needs to be multiplied by $(1/(1-\rho))$ to obtain the appropriate effect of a change in the explanatory variable on the dependent variable[13]. The first thing to note is that the estimated ρ is positive and highly statistically significant, indicating that if teen employment is high in one county it will be high in neighboring counties. The specific estimate of 0.49 indicates that employment in one county, on average, is equal to 49% of the weighted average of surrounding counties' employment. This result is consistent with the idea of agglomeration economies leading firms to locate close to one another and to create employment centers that may cross county boundaries. Note also that the estimated coefficient on the effective minimum wage variable is even larger than the OLS estimate, suggesting that an increase in the effective minimum wage of 10% leads to a reduction in youth employment of 3.2%. This result is at the higher end of the range of negative estimates in the literature and is 28% higher than the OLS estimate, a substantial increase, suggesting that estimates that do not take into account spatial correlation may be significantly underestimating the negative effect of the minimum wage on teenage employment. The estimated effects for several other variables are also affected when spatial correlation in the dependent variable is controlled. For example, the percent less than high school variable, which

[13] Kim et al. (2003) derive the procedure for this marginal effect calculation. The $(1/(1-\rho))$ term is referred to as a spatial multiplier and is the effect if a unit change were induced at every location.

Table 3 SAC regression estimates[a]

Explanatory variables	Estimated coefficient	t Statistic
Constant	−5.12	−14.41***
ln(minimum wage)	−0.17	−1.95*
ln(per capita income)	0.42	12.45***
ln(average weekly wage)	−0.19	−7.57***
Adult male unemployment rate	−0.02	−10.09***
ln(percent white)	0.28	15.09***
ln(percent with less than high school degree)	0.04	2.03**
ln(percent with high school degree)	0.24	8.31***
ln(percent with college degree)	0.10	4.31***
ln(percent with graduate degree)	−0.04	−3.10***
Percent rural	−0.002	−13.86***
ρ	0.46	17.98***
λ	0.04	0.89
Number of observations	3,065	
Adjusted R^2	0.64	

Dependent variable: log of youth employment to population ratio
*Significant at the 10% level
**Significant at the 5% level
***Significant at the 1% level
[a] The SAC model was estimated using the generalized method of moments technique of Kelejian and Prucha (1998).

was statistically insignificant in the OLS specification, becomes statistically significant in the SAR specification. Also, the estimated marginal effect of an increase in per-capita income also increases by a substantial 45%, from 0.55 to 0.80 when one moves from the OLS to SAR specification.

Table 4 SAR regression estimates

Explanatory variables	Estimated coefficient	t Statistic
Constant	−5.18	−21.71***
ln(minimum wage)	−0.16	−2.12**
ln(per capita income)	0.41	12.13***
ln(average weekly wage)	−0.19	−8.19***
Adult male unemployment rate	−0.02	−10.20***
ln(percent white)	0.27	15.67***
ln(percent with less than high school degree)	0.04	2.40**
ln(percent with high school degree)	0.23	10.07***
ln(percent with college degree)	0.10	5.50***
ln(percent with graduate degree)	−0.04	−3.17***
Percent rural	−0.002	−14.01***
ρ	0.49	14.97***
Number of observations	3,065	
Adjusted R^2	0.56	

Dependent variable: log of youth employment to population ratio
*Significant at the 10% level
**Significant at the 5% level
***Significant at the 1% level

Conclusions

The effects of the minimum wage have been studied using many different data sets and methods of controlling for omitted geographic factors. The results of this study are novel for two reasons. First, county-level, rather than state-level, data are utilized in the empirical analysis. Second, spatial econometric techniques are employed to capture any unobserved factors that may be correlated across geographic space. The results of the SAR model indicate that a 10% increase in the minimum wage is associated with a 3.2% decrease in youth employment, an estimate that is at the higher end of the range of negative estimates in the literature and is 28% higher than our OLS estimate, a substantial increase. They also indicate that employment in one county is positively associated with neighboring counties, perhaps because of agglomeration economies or other geographical features that lead to concentrations of employment.

Our results indicate that spatial autocorrelation must be accounted for when estimating the effect of the minimum wage or of any policy that may be affected by omitted geographic factors. Researchers interested in obtaining accurate estimates should explore the possibilities offered by spatial econometric techniques.

Acknowledgements The authors would like to thank Diana Castillo-Trejo and Adam Lucchesi for their excellent research assistance.

References

Anselin L (1988) Spatial econometrics: methods and models. Kluwer Academic Publishers, Dordrecht

Anselin L (2001) Spatial econometrics. In: Baltagi B (ed) A companion to theoretical econometrics. Blackwell, Oxford

Anselin L, Bera A (1998) Spatial dependence in linear regression models with an introduction to spatial econometrics. In: Ullah A, Giles DEA (eds) Handbook of applied economic statistics. Marcel Dekker, New York

Anselin L, Bera A, Florax R et al (1996) Simple diagnostic tests for spatial dependence. Reg Sci Urban Econ 26(1):77–104

Card D (1992a) Using regional variation in wages to measure the effects of the federal minimum wage. Ind Labor Relat Rev 46(1):22–37

Card D (1992b) Do minimum wages reduce employment? a case study of California, 1987–89. Ind Labor Relat Rev 46(1):38–54

Card D, Kreuger A (1994) Minimum wages and employment: a case study of the fast-food industry in New Jersey and Pennsylvania. Am Econ Rev 84(4):772–793

Card D, Krueger A (2000) Minimum wages and employment: a case study of the fast-food industry in New Jersey and Pennsylvania: reply. Am Econ Rev 90(5):1397–1420

Dubin R (1998) Spatial autocorrelation: a primer. J Hous Econ 7(4):304–327

Florax R, Folmer H, Rey S (2003) Specification searches in spatial econometrics: the relevance of Hendry's methodology. Reg Sci Urban Econ 33(5):557–579

Kalenkoski C, Lacombe D (2006) Right-to-work laws and manufacturing employment: the importance of spatial dependence. South Econ J 73(2):402–418

Kelejian H, Prucha I (1998) A generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances. J Real Estate Finance Econ 17 (1):99–121

Kim C, Phipps T, Anselin L (2003) Measuring the benefits of air quality improvement: a spatial hedonic approach. J Environ Econ Manag 45(1):24–39

Lee L (2004) Asymptotic distributions of quasi-maximum likelihood estimators for spatial autoregressive models. Economics 72(6):1899–1925

Lianos T (1972) Impact of minimum wages upon the level and composition of agricultural employment. Am J Agric Econ 54(3):477–484

Michl T (2000) Can rescheduling explain the New Jersey minimum wage studies? East Econ J 26 (3):265–276

Neumark D, Wascher W (1992) Employment effects of minimum and subminimum wages: panel data on state minimum wage laws. Ind Labor Relat Rev 46(1):55–81

Neumark D, Wascher W (1995) Minimum wage effects on employment and school enrollment. J Bus Econ Stat 13(2):199–206

Neumark D, Wascher W (2000) A case study of the fast-food industry in New Jersey and Pennsylvania: comment. Am Econ Rev 90(5):1362–1396

Neumark D, Wascher W (2006) Minimum wages and employment: a review of evidence from the new minimum wage research. NBER Working Paper No. 12663

Partridge M, Partridge J (1998) Are teen unemployment rates influenced by state minimum wage laws? Growth Change 29(4):359–382

Partridge M, Partridge J (1999) Do minimum wage hikes reduce employment? State-level evidence from the low-wage retail sector. J Labor Res 20(3):393–413

Schiller B (1994) State minimum wage laws: youth coverage and impact. J Labor Res 15(4):317–329

Wessels W (1993) The minimum wage and tipped employees. J Labor Res 14(3):213–226

Williams N (1993) Regional effects of the minimum wage on teenage employment. Appl Econ 25 (12):1517–1528

Zavodny M (2000) The effect of the minimum wage on employment and hours. Labour Econ 7 (6):729–750