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Local Labor Markets and Child Poverty*

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Abstract

This study uses modeled Small Area Estimates data to analyze the labor market influences on child poverty rates in local areas. These data support analysis of small geographic areas as well as at different points of the business cycle. Statistical tests appropriate for data with geographic and intertemporal correlations are adapted for use with modeled data. The results reveal that child poverty rates in local areas vary with the diversity of the local economy, specifically with dependence on a particular industry and with the diversity of firm size. These influences have varying impact at different points of the business cycle.

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1. INTRODUCTION

The spatial variation in child poverty rates is influenced by a number of labor supply and labor demand factors. Friedman and Lichter (1998) have used the local demographic composition, educational attainment, and the proportion of female-headed households as measures of labor supply. They measure labor demand with the local unemployment rate, the "underemployment" rate, and the mix of employment across industries.

This and similar studies of the spatial variation in child poverty rates have, by coincidence, been focused on time periods around business cycle peaks. The decennial census, the primary data for such analysis, has occurred near the cyclical peaks in January 1980 and July 1990. The next decade of analysis will be similar since the 2000 census occurred relatively near a peak in March 2001.[1]

Alternative data sources with more frequent reference periods are available but do not have adequate sample sizes for analysis of small geographic areas. The Current Population Survey (CPS), for example, can be used to analyze variation in poverty in Metropolitan Statistical Areas (MSAs) but not in rural areas.

This study demonstrates that modeled small area estimates (SAE) data can be used to analyze the spatial distribution of child poverty. SAE data have the advantages of both the decennial census and the CPS; they cover the entire United States and are available for different points in the business cycle. The county is the unit of analysis.

As one of the influences on child poverty rates, local economic diversity is included in the analysis in several ways. We analyze the dependence of the local economy on particular industries based on a typology of rural counties. Also, the variation in the size of the local firms is a previously unutilized and important measure of local economic diversity.

The influences of these and other factors are tested using a multivariate logistic regression. Because standard significance tests are not appropriate for use with SAE data, we employ a variant of a technique previously used for survey data with a complex sample design. A discussion of this technique is given in Sections 3.1 and 3.2.

2. LITERATURE REVIEW

2.1 Geographic Measurement Issues

The choice of the best unit of geography for analysis of child poverty issues is restricted to the available administrative units. Some influences on well-being could be on the family or neighborhood level. In this case, measurement of these influences should be on the smallest administrative unit possible. By contrast, the most relevant unit for economic influences is the labor market.

Labor markets can be defined as clusters of counties within which people are frequently observed commuting (U.S. Department of Labor 2003). In urban areas, the labor market

[1] The American Community Survey will also provide data relevant to this issue.

definitions correspond to MSAs, which are groupings of counties.[2] In rural areas, the labor market is usually congruent to the county, although some rural counties are also aggregated into labor markets based on commuting patterns.

This operational definition of labor markets can be used to analyze poverty in MSAs because they are a component of the domain or strata of many household surveys, but the surveys do not generally have enough sample to support analysis in rural counties. MSA level studies include Rexroat (1989), Eggers and Massey (1991), Bartik (1994), Freeman and Rodgers III (1999) , Hoynes (2000), and Madden (2000). These studies generally focus on the distribution of income, with analysis of poverty as a secondary concern and without separate analysis of child poverty.

The labor market or the MSA are appropriate units of analysis for the general study of the distribution of income but may be too large for the study of child poverty. Labor market definitions based on commuting patterns may be too large for the study of people with children and no or little income. While it is clear that families with children are less mobile (Long 1972), it is not immediately clear whether the poor are also less mobile. For example, the evidence on whether the poor have a smaller commuting range or are less willing to migrate is mixed. Using tabulations by income, city size, and time of commute, Gordon, Kumar, and Richardson (1989) find a positive relationship between income and commuting time only for peak time commutes in large cities. In a multivariate analysis controlling for these and other factors, however, Taylor and Ong (1995) find a general positive relationship.[3] For residential mobility, there is limited evidence of a general relationship between income and the tendency to migrate, however, poor people who are on public assistance are less willing to migrate (Frey et al. 1998, Long 1988, and Nord 1998).

The study of the distribution of poor children thus requires a smaller unit of analysis. Several studies analyze the determinants of poverty on the county level. Tomaskovic-Devey (1987), Colclough (1988), and Levernier and White (1998) analyze the determinates of adult poverty in particular states while Weinberg (1987) and Tickamyer and Duncan (1990) analyze rural counties. The only studies covering all counties in the U.S. are Friedman and Lichter (1998) and Levernier, Partridge, and Rickman (2000). The study by Friedman and Lichter is the only one we know of to analyze child poverty in all U.S. counties.

2.2 The Influences on Child Poverty Rates

Friedman and Lichter (1998) include variables capturing the influences that are common in the poverty literature. Family structure—specifically the number of adult potential earners—is an important influence. Some authors, such as Gottshalk and Danziger (1993) and Lerman (1996), ascribe a primary role in determining the level of poverty to family structure as measured by the proportion of female-headed households. However, Friedman and Lichter note that local poverty varies much more than local family structure; it is thus only a complementary factor. They nevertheless include the proportion of female-headed households as a statistically significant variable in their study, as is standard in poverty studies. Demographic indicators including the proportion of the population that is black and the proportion Hispanic are also

[2] Minor civil divisions and county equivalents are also used.

[3] Additionally, residential segregation within a labor market may place the available opportunities outside the commuting range of poor families (Stoll, Holzer, and Ihlanfeldt 2000).

standard variables. Both are generally positively associated with poverty, although a negative association is sometimes found for poverty among adults (Levernier, Partridge, and Rickman 2000). The proportion of people with less than a high school education is usually positively associated with child poverty.

Variables measuring local differences in labor demand are also common. Friedman and Lichter (1998) include the unemployment rate and the "underemployment" rate, which is a measure of the proportion of employment that is part-time or intermittent. Bartik (1996) argues that employment levels are a more accurate indicator while Levernier, Partridge, and Rickman (2000) use a variety of measures but emphasize changes in employment levels over time.

Variables that control for industry concentration of either employment or output are also standard. There are two reasons why industry concentration could be associated with local well-being. Katz and Summers (1989) argue that differences in productivity allow firms in some industries to pay efficiency wage differentials. In other words, the effect on well-being is primarily through higher wages. Alternatively, concentration in one particular industry may indicate a lack of diversity in the local economy. Siegel, Johnson, and Alwang (1995) provide a comprehensive review of the theory and measurement of economic diversity. Lack of diversity may lead to instability in the local economy, intermittent employment, and an unsteady development of human capital. Siegel, Johnson, and Alwang argue that industry composition can be conceptualized as an element of a region's portfolio diversity similar to an individual's portfolio of investments.

The measure of diversity employed by Friedman and Lichter (1998), industry concentration, is just one of many possible measures (Siegel, Johnson, and Alwang 1995). Cook and Mizer (1994) propose specific degrees of concentration above which a locality can be thought of as being dominated by one particular industry. The cutoffs are based on analysis of the distribution of labor and property income by industry and form mutually exclusive categories.

Regardless of theoretical explanation, there is general agreement about the empirical correlation of poverty and specific industries. For example, a concentration in mining is associated with higher poverty (Friedman and Lichter 1988, Tickamyer and Duncan 1990). Also, Levernier, Partridge, and Rickman (2000) report that a concentration in agriculture is associated with higher poverty, and Tomascovic-Devey (1987) confirms this for counties in the state of South Carolina. By contrast, a concentration in manufacturing is associated with lower poverty (Friedman and Lichter 1998, and Weinberg 1987). The impact of a concentration in services depends on the classification system used (Friedman and Lichter 1998, Levernier, Partridge, and Rickman 2000).

Although not previously considered, there is reason to believe that firm size also affects local well-being. The theoretical explanations mirror the explanations for industry concentration. One explanation is that large firms pay higher wages. Oi and Idson (1999) review the theoretical reasons why larger firms pay higher wages and the empirical evidence. Firms may pay efficiency wages to avoid monitoring costs or to deter shirking. Or, large firms may have higher profits due to monopoly powers and engage in rent sharing. Regardless of reason, there is significant empirical evidence that large firms do pay higher wages.

An alternative theoretical explanation of the role of large firms is compatible with portfolio diversification. Large firms may offer a diversity of employment opportunities by offering durable employment (Idson 1996) and thus add income stability to the local economy (Siegel, Johnson, and Alwang 1995). Theoretical explanations include the ability of large firms to substitute intrafirm mobility for interfirm mobility or lower firm failure rates (Idson 1996). In addition, large firms tend to have personnel policies that discourage turnover such as rewarding seniority (Oi and Idson 1999) or offering pensions (Even and MacPherson 1996). There is also overwhelming empirical evidence of the relation between turnover and firm size (Even and MacPherson 1996).

The measures of industry concentration and firm size are compatible with different conceptual explanations. Efficiency wage theory connects both measures to local well-being via the mechanism of higher wages. On the other hand, both measures could capture local economic diversity. This study provides empirical evidence about the explanatory power of the competing theories.

3. METHODS

3.1 Small Area Estimates (SAE) Poverty Data

SAE poverty data were created by the Census Bureau using a modeling process. Three adjacent years of CPS data were combined into initial estimates of county-level poverty. The initial estimates were of varying quality because some of them are based on only a few CPS observations. Next, the initial estimate was the dependent variable in a predictive equation using a variety of county-level indicators of poverty. For 1995, 1,271 counties had observations in the CPS that were used to get predictions for all 3,141 counties. Using empirical Bayes (or "shrinkage") techniques, the predicted values were combined with the initial estimates. The weight of each component was proportional to its relative precision. This process results in estimates that are more precise than the alternatives without biases along important dimensions such as race or urbanicity (Citro and Kalton 1999).

In general terms, the Census Bureau creates the SAE data using a linear model with fixed and random effects. The structure of the random effects is borrowed from analysis of 1990 census data (Fisher 1997). The fixed effects derive from a variety of sources, including tabulations of child exemptions reported on tax returns for families that were poor, the frequency of food stamp recipiency, population estimates, and poverty data from the census.

Use of these data has several complications for the purposes of this study. It is essential that the variables used in the logistic regression for this analysis are not the same as or highly correlated with the variables used to create the data. Also, statistical tests designed for use on data created by simple random sampling are not appropriate for modeled data.

The SAE data does not meet the assumptions upon which logistic regression is based. This is generally true for survey data, and several papers address this problem (see Fay 1985; Rao, Wu, and Yue 1992; and Sitter 1992, for example). The CPS, on which the SAE data are based, has clustering in the sample design that causes spatial correlations in the data. The result of ignoring these correlations is a tendency to exaggerate the size of the estimated differences relative to the random variation (type I error). For example, all the coefficients presented later in the paper except one would be significant at the 1 percent level of significance if the logistic regression coefficients were tested using standard tests.

This case has the additional complication that the child poverty data are the result of a modeling process. The models that produce the child poverty data have inputs that overlap in three year intervals. This creates correlations across time in child poverty data that are two years apart. Again, this feature will tend to exaggerate the results of significance tests.

The work of Roberts, Rao, and Kumar (1987) is relevant to this problem. They derive estimates of the variances of logistic regression parameters when analysis is based on survey data. However, the technique requires a separate estimate of the covariances in the dependent variable, including variances and covariances across space and time.

These correlations are not available in this case, so the technique had to be modified. The correlations across space are inherent in data that are produced by predictive models and can be derived from the variance of the modeling coefficients (Fisher, 1997). Estimates of the correlations across time were based on published information about the sampling rotation in the underlying CPS data (Bell, 1999).

The resulting estimates provide conservative tests of the significance of the logistic regression parameters. The tests are an improvement over unmodified tests but should be viewed as approximations that have not accounted for all sources of variance relevant to hypothesis testing.

3.2 Modification of the Technique of Roberts, Rao, and Kumar (1987)

We use a variant of the approach followed by Roberts, Rao, and Kumar (1987). They developed a logistic regression for use when survey data bears little resemblance to a random sample. The estimated domain relative size (poor children in counties by poverty status, in our case), $w_i = \hat{N}i/\hat{N}$, is used in place of the usual observed proportion in a random survey, n_i/n, to form a "pseudo" likelihood. This is then maximized to obtain estimates of the interesting parameters and poverty probabilities. This is the same general form that we use, except in our problem the response variable is the SAE estimate, which is model-based. Roberts, Rao, and Kumar assume the existence of a survey estimate of the covariance matrix of the response variable $\boldsymbol{V}$. Their estimator for the variance of the logistic regression coefficients is

$$(1) \qquad V\,(\hat{\beta}) = n^{-1}\left(X'\hat{\Delta}X\right)^{-1}\left[X'D(w)\,\hat{V}\,D(w)\,X\right]\left(X'\hat{\Delta}X\right)^{-1}$$

where

$$(2) \qquad \hat{\Delta} = diag\left(w_1\hat{f}_1\left(1-\hat{f}_1\right),\ldots,w_I\hat{f}_I\left(1-\hat{f}_I\right)\right)$$

f_i is the poverty probability by county, hat denotes an estimate, and $\hat{V} * n^{-1}$ is the estimate of the variance from the survey or, in this case, the SAE model-based estimates.

They use the assumption that the response variable is consistent and converges in distribution to a normal distribution. We can claim that the same assumptions hold for the SAE estimates, given that the modeling assumptions hold. It remains to obtain an expression for $\boldsymbol{V}$, which is composed of the within-year covariance matrices, $\boldsymbol{V}_i$, $I = 89$, 93, 95 and the between-year covariance matrices, $\boldsymbol{C}_{ij}$.

Variance estimation for the SAE estimates is discussed by Fisher (1997); these results lead to the within-year covariance matrices. Further results by Bell (1999) lead to between-year covariances of the prediction errors.

The SAE model predicted the log numbers of poor people as a linear function of the covariates. Since the number of interest is actually the number of poor, the exponential was used. The Taylor expansion of the exponential function was used to derive an approximate variance for the estimated number of poor. As a final step, the SAE estimates were forced to sum to the independently modeled state estimates by a simple ratio adjustment. The effects of this adjustment are neglected in this analysis.

Given the final estimates of ***V***(), the Wald hypothesis tests are available (again, see Roberts, Rao, and Kumar); these are the tests we used in this analysis.

3.3 Estimating Equation

This study analyzes three years of data. Corresponding to the recession in the early 1990s, we chose the year 1993 because it had the highest national child poverty rate since the early 1970s. After 1993, child poverty declined steadily until the recession in the early 2000s; 1995 is a representative year from that period. A cyclical low in child poverty occurred in 1989, which coincided with the business cycle peak in 1990. This year also provides a basis for comparison to previous studies that utilized the 1990 Census.

The model stacked these three years of data for use in a logistic regression framework. We controlled for the effects of national economic conditions by using intercepts for the different years of analysis. We controlled for the effects of local labor market conditions by including the unemployment rate in the county as measured by the Local Area Unemployment Statistics program of the U.S. Bureau of Labor Statistics. These data are also the result of a modeling process; however, the correlations created by this modeling are neglected in this analysis and may be addressed in future research.

The central variables of interest are those that relate to local economic diversity. We employ the county typology proposed by Cook and Mizer (1994) as a classification of rural counties. For example, a manufacturing-dependent county is defined as one where 30 percent or more of the total labor and property income is generated in the manufacturing sector. The typology is based on the empirical distribution of labor and property income across industries and results in mutually exclusive categories. We include dummy variables for manufacturing, farming (20 percent cutoff), mining (15 percent), government (25 percent), and service-dependent counties (50 percent). We implicitly assume that metropolitan counties are more economically diverse than rural counties and thus do not classify metropolitan counties. We do distinguish between metropolitan counties that are classified as located in the central city and other. We include dummy variables for central city metropolitan counties and for non-metropolitan counties. The omitted group is metropolitan counties, not central city.

We employ a measure of firm size as an additional measure of economic diversity. We reason that all counties have small firms but that having large firms creates additional employment opportunities and demand for specialized labor. The variable is defined as the percentage of firms employing more than 500 people as measured in the Regional Economic Information System of the U.S. Bureau of Economic Analysis. Firms of this size are relatively rare since the mean number of such firms is 0.16 percent per county; however, counties can have up to 5 percent of such firms. The standard deviation of this measure is less than 0.25 percent, thus one percentage point represents more than four standard deviations. As a result, we expect the coefficient on this variable to be on a different scale from some of the other variables where one percentage point represents a fraction of a standard deviation.

TABLE 1

Means and Standard Deviations of Variables, All U.S. Counties

Variable	Income year 1989, Survey year 1990	Income year 1993, Survey year 1994	Income year 1995, Survey year 1996
Number of poor children (age < 18)	4,022	5,012	4,672
	(17,497)	(23,580)	(21,695)
Number of children (age < 18)	20,316	21,675	21,988
	(67,238)	(72,738)	(73,496)
Unemployment rate (%)	6.2	7.0	6.0
	(2.9)	(3.3)	(3.1)
Female-headed households (%)	12.8	—	—
	(5.4)	—	—
Average wage per job ($thousands)	17.3	20.0	21.2
	(3.9)	(4.5)	(4.7)
Large firms (%)	0.153	0.158	0.168
	(0.232)	(0.219)	(0.228)
Black (%)	8.6	—	—
	(14.3)	—	—
Hispanic (%)	4.4	—	—
	(11.0)	—	—
Less than high school (%)	30.4	—	—
	(10.4)	—	—
Work outside county (%)	27.8	—	—
	(17.4)	—	—
Metropolitan, central county	—	15.8	—
(% of counties)	—	(36.4)	—
Non-metropolitan county	—	74.2	—
(% of counties)	—	(43.8)	—
Non-metropolitan county typology:			
Manufacturing (% of counties)	—	16.2	—
	—	(36.8)	—
Farming (% of counties)	—	17.7	—
	—	(38.2)	—
Government (% of counties)	—	7.7	—
	—	(26.7)	—
Mining (% of counties)	—	4.6	—
	—	(21.0)	—
Services (% of counties)	—	10.3	—
	—	(30.4)	—
South division (% of counties)	—	—	45.5
	—	—	(49.8)

Standard deviations are in parentheses. "— " means that data are not available for that year.

We also include the standard control variables discussed above from the 1990 census, including the percent of female-headed households, the percent black, the percent Hispanic, and the percent with less than a high school education. We add a variable measuring the percent of the employed who commute to outside the county in order to acknowledge that employment opportunities in nearby counties affect local well-being. These variables do not change for the different years of analysis; however, the demographic composition of a county and its commuting patterns are not expected to change greatly over the six-year period of analysis.

We also employ a measure of the wage level in order to control for possible efficiency wage differentials. The average wage per job in a county is also available from the Regional Economic Information System of the U.S. Bureau of Economic Analysis.

Table 1 gives the means and standard deviations for the analysis variables across counties. In the estimating equation, most of the variables are also interacted with the year of analysis dummy variables in order to test whether the influence varies at different points of the business cycle. Dummy variables for 1993 and 1995 are used while 1989 is the omitted group. The interaction terms highlight differences from previous studies that analyze only 1989. Also, the percent of female-headed families is interacted with some of the demographic and geographic variables to test whether the effect is localized to particular areas or groups.

4. INTERPRETATION OF EMPIRICAL RESULTS

4.1 Logistic Regression Results

Table 2 shows the logistic regression coefficients, standard errors, and chi-squared statistics for the modified significance tests. The critical value of the chi-squared statistic at the 5 percent level of significance is 3.84. The dependent variable is the log odds ratio (Menard 1995) of a child being in poverty in a county for children less than 18 years of age.

We structured the model to control for national and local labor demand factors. The dummy variable for the year 1993 shows that child poverty is higher in 1993 than in 1989, *ceteris paribus*. The same is true for 1995, although the magnitude is smaller. This reflects the arc of the cycle in national economic conditions during this time period.

We controlled for local economic conditions with the local unemployment rate. The coefficient and significance test show that more unemployment is associated with more child poverty. The interaction terms with the year dummy variables are negative, indicating that the influence of the unemployment rate is smaller in 1993 and 1995 than in 1989, although only 1995 is statistically significant. While the regression coefficients are mathematically informative, they are difficult to interpret. We therefore present the results as odds ratios in Table 3. Odds ratios are related to the regression coefficients through the exponential function (Menard). The odds ratios show that one percent higher unemployment is associated with 2.3 percent higher odds of a child being in poverty in 1989 when other factors are held constant. This is smaller than the magnitude reported by Friedman and Lichter (1998) for 1989.[4] In addition, there is a secular decline in the influence of the unemployment rate. In 1993, the magnitude declines to 2.0 percent, and it declines further to 1.4 percent in 1995.

[4] The partial derivative of the change in unemployment to the change in child poverty is 0.45, versus 1.0 for Friedman and Lichter (1998).

TABLE 2

Regression Coefficients

Variable	Coefficient	Standard error	Chi-squared
Intercept	-2.809***	0.109	654.57
1993 = 1	0.291***	0.077	15.29
1995 = 1	0.255***	0.086	8.88
Unemployment rate	0.023***	0.003	83.12
Unemployment rate & 1993 = 1	-0.004	0.004	0.96
Unemployment rate & 1995 = 1	-0.009**	0.005	4.19
Female-headed households	0.074***	0.008	80.12
Female-headed &1993 = 1	0.001	0.003	0.10
Female-headed & 1995 = 1	-0.004	0.004	1.19
Metropolitan, central county	-0.011	0.111	0.01
Metropolitan, central & 1993 = 1	0.060	0.063	0.88
Metropolitan, central & 1995 = 1	0.065	0.074	0.77
Non-metropolitan county	0.232**	0.106	4.83
Non-metropolitan & 1993 = 1	0.014	0.061	0.05
Non-metropolitan & 1995 = 1	0.000	0.070	0.00
Central * female headed	-0.007	0.008	0.72
Non-metropolitan * female- headed	-0.021***	0.008	6.75
Manufacturing	-0.078***	0.018	19.36
Manufacturing & 1993 = 1	-0.015	0.030	0.28
Manufacturing & 1995 = 1	0.040	0.034	1.34
Farming	0.139***	0.017	64.77
Farming & 1993 = 1	-0.206***	0.030	48.31
Farming & 1995 = 1	-0.106***	0.034	9.60
Government	0.086***	0.021	17.05
Government & 1993 = 1	-0.068*	0.036	3.49
Government & 1995 = 1	0.015	0.042	0.12
Mining	0.116***	0.031	14.04
Mining & 1993 = 1	-0.041	0.053	0.61
Mining & 1995 = 1	0.039	0.061	0.37
Services	0.069***	0.018	14.92
Services & 1993 = 1	-0.073**	0.031	5.57
Services & 1995 = 1	0.012	0.036	0.12
Large firms	-0.627***	0.033	359.36
Large firms & 1993 = 1	0.307***	0.056	30.06
Large firms & 1995 = 1	0.199***	0.057	12.06
Black	0.003***	0.001	18.30
Black & 1993=1	0.000	0.001	0.06
Black & 1995=1	0.002	0.001	1.13
Black & female-headed households	0.000***	0.000	51.45
Hispanic	0.004***	0.000	75.36
Hispanic & 1993 = 1	0.001	0.001	2.62
Hispanic & 1995 = 1	0.002***	0.001	7.40
Less than high school	0.031***	0.001	1214.16
Less than high school & 1993 = 1	-0.008***	0.001	29.56
Less than high school & 1995 = 1	-0.005***	0.002	9.33
Work outside county	-0.011***	0.000	778.52
Work outside county & 1993=1	0.002***	0.001	7.72
Work outside county & 1995=1	0.001*	0.001	3.44
South division	0.027*	0.015	3.36
South division & 1993 = 1	0.028	0.026	1.05
South division & 1995 = 1	0.066**	0.030	4.84
Average wage per job	-0.014***	0.002	77.76

***Statistically significant at the 1% level, ** Statistically significant at the 5% level, * Statistically significant at the 10% level

TABLE 3

Odds Ratios, Child Poverty Rate

Variable	All years	1993	1995
Intercept	0.060***	0.081***	0.078**
Large firms	0.534***	0.726***	0.652***
Metropolitan, central county	0.989	1.051	1.056
Non-metropolitan county	1.261**	1.279	1.261
Non-metropolitan county typology:			
Manufacturing	0.925***	0.910	0.962
Farming	1.150***	0.935***	1.034***
Government	1.109***	1.019*	1.106
Mining	1.123***	1.078	1.165
Services	1.072***	0.996**	1.059
Unemployment rate	1.023***	1.020	1.014**
Female headed households	1.077***	1.078	1.072
Metropolitan, central * female-headed	0.993	—	—
Non-metropolitan * female-headed	0.979***	—	—
Black	0.997***	0.996	0.998
Black & female-headed households	1.000***	—	—
Hispanic	1.004***	1.005	1.006***
Less than high school	1.032***	1.024***	1.026***
Work outside county	0.898***	0.991***	0.991*
South division	1.028*	1.056	1.098**
Average wage per job	0.986***	—	—

***Statistically significant at the 1% level, ** Statistically significant at the 5% level, * Statistically significant at the 10% level

The labor supply variables confirm the results of previous studies. The percentage of a county that is Hispanic or has less than a high school education is associated with more child poverty, while the percentage that is black is associated with less. The percentage of female-headed households has a positive impact, and the magnitude is greater than the other labor supply factors.

The interaction terms reveal that the influence of the percent of female headed households varies little over time, race, or urbanicity. The influence of this variable does not vary significantly over the years of analysis as demonstrated by the interaction terms with the year variables. The interaction of female-headed households with black is statistically significant although not economically significant because the odds ratio is one. Similarly, the influence is not greater in central counties in metropolitan areas. Only the interaction of female-headed households with non-metropolitan counties reveals a meaningful difference; the percent of female-headed households is less strongly associated with child poverty in non-metropolitan areas.

Two other variables can be thought of as control variables. The coefficient for the percent of people who work outside the county is small but important. One standard deviation is around 17 percentage points for this variable; thus the odds of poverty differ by around 21 percent for counties that differ by one standard deviation for this variable. The coefficients for the Census South division reveal consistently higher and increasing child poverty for these seventeen states relative to the rest of the country.

The variables of most interest are the variables for local economic diversity. The variables representing the rural county typology confirm the results of previous studies; a concentration in farming, government, mining, or services is associated with more child poverty, while a concentration in manufacturing is associated with less. The model also provides estimates of whether the effects of industry dependence vary at different points in the business cycle. For farming- and service-dependent counties, the relative disadvantage of industry dependence was ameliorated during the recession. In fact, a concentration in farming or services became a small relative advantage during the recession. Perhaps agricultural business cycles are different from the general business cycle to the extent that this provides portfolio diversification. Similarly, the service industry may be a diverse category in itself or this may reflect that some services such as medical care are income inelastic (Van Vliet 2001). While the negative effects were eliminated in farming- and service-dependent counties during the recession, the advantage of manufacturing-dependent counties did not decrease significantly. Previous studies have found evidence that sales of durable goods are more cyclical than other goods (Cook 1999, for example), however, our results do not confirm this. The impact of dependence on manufacturing on child poverty did not decrease significantly during the recession of the early 1990s.

The other possible measure of economic diversity is the variable for the percentage of large firms. An increase in the percentage of large firms is clearly a benefit to the poverty status of local children. As explained above, the odds ratio of 0.53 for 1989 is a result of the rarity of large firms. If we examine a difference of one standard deviation rather than one percentage point, the corresponding difference in the odds of child poverty is 16 percent. In addition, the benefit of large firms was reduced during the recession. This suggests that large firms have strong local poverty benefits but that they are more vulnerable than average to cyclical influences. This result would need confirmation with time series analysis.

The coefficient on the average wage per job shows that poverty decreases as the average wage increases, as expected. A county with one standard deviation higher average wages (about $4,000 per year) has about a 5 percent lower odds of child poverty. The purpose of including this variable is to estimate the effects of key variables net of the influence of the wage level. For example, part of the influence of large firms is due to higher wages, perhaps due to efficiency wage differentials. By controlling for the wage level, we isolate the remaining benefits to a county of having large firms. The results discussed previously show that there are remaining benefits.

4.2 Limitations

It is important to note that the logistic regression coefficients and significance tests may suffer from omitted variable bias. One possibility is that large firms offer benefits to the employee in addition to higher average wages. Components of the indirect compensation package could indirectly affect poverty. For example, the prevalence of health insurance may affect a locality's poverty level even though health insurance benefits are not measured in the official poverty measure. In the case of indirect compensation, the influence of the variables capturing economic diversity could be exaggerated by being correlated with the omitted variable. We offer a preliminary test designed to reveal the scope of the possible problem. We show that the important results are robust with respect to inclusion or exclusion of the (average) direct wage and hypothesize that they would also be robust with respect to inclusion or exclusion of indirect compensation items. The direct wage is the largest component of compensation, thus the preliminary test may indicate an upper bound on the scope of the possible problem.

The results are shown in Table 4, which contains selected odds ratios corresponding to the original specification, as well as the alternate specification, which excludes the average wage. The odds ratios for the year interaction terms are excluded for clarity of exposition. The odds ratios corresponding to the variables measuring economic diversity are quite robust; including the additional variable does not change the magnitudes of the relevant odds ratios in any systematic way.

Omitted variable bias could also be a problem in a broader sense. There are likely to be omitted factors in counties that cause the child poverty levels to be correlated across years. This correlation is neglected in this analysis but may be considered in future research. However, we believe the size of this bias to be substantially smaller than the biases for which we control. The adjustments to the standard errors described above sometimes changed the value of the chi-

TABLE 4

Selected Odds Ratios for the Basic and Alternate Specifications

Variable	Original specification All years	Alternate specification All years
Intercept	0.060***	0.041***
Large firms	0.534***	0.465***
Metropolitan, central county	0.989	0.871
Non-metropolitan county	1.261**	1.208**
Non-metropolitan county typology:		
Manufacturing	0.925***	0.945***
Farming	1.150***	1.242***
Government	1.090***	1.109***
Mining	1.123***	1.084***
Services	1.072***	1.108***
Unemployment rate	1.023***	1.029***
Female-headed households	1.077***	1.080***
Metropolitan, central * female-headed	0.993	0.999
Non-metropolitan * female-headed	0.979***	0.982***
Black	0.997***	1.005***
Black & female headed households	1.000***	1.000***
Hispanic	1.004***	1.002***
Less than high school	1.032***	1.034***
Work outside county	0.989***	0.990***
South division	1.028*	1.039**
Average wage per job	0.986***	—

***Statistically significant at the 1% level, ** Statistically significant at the 5% level, * Statistically significant at the 10% level squared statistic by one order of magnitude. In contrast, when Levernier, Partridge, and Rickman (2000) controlled for correlations across time with a state-level fixed effect, the effect on the coefficients explaining adult poverty levels were modest.

Another concern is multicollinearity between the average wage and the other analysis variables. Although we saw no gross correlations in the data that caused concern, the average wage has been theoretically and empirically tied to many of the variables we use. For example, wages vary by firm size, urban or rural location, industry, family structure, and educational attainment. Table 4 shows, however, that multicollinearity does not affect the significance tests in this case. Including or excluding the average wage does not change the results of the significance tests, with only one exception (South Census region).

5. CONCLUSION

Small area estimates data can be used to analyze the influences on local child poverty rates. The poverty status of a county's children is closely tied to the county's demographic characteristics, family structure, and education level. The local and national economic cycle are also important. Having accounted for these factors, however, a variation remains that is correlated with industrial structure and the composition of firms.

Part of the remaining variation can be interpreted as the efficiency wage differentials paid by large firms and firms in particular industries. The higher wages paid by large firms, particularly large manufacturing firms, have a poverty-reducing effect. However, this is only a portion of the remaining variation. Correlations between poverty and firm size and between poverty and industrial concentration remain, even when controlling for the wage level. We attribute the remaining correlation to the effects of local economic diversity.

Areas with large firms are more diverse than areas with only small firms, and a greater diversity of firm size is associated with lower child poverty. By contrast, a lack of diversity as measured by concentration of economic activity in one particular industry is associated with greater child poverty. A concentration in manufacturing industry, which is associated with lower child poverty, is the one exception.

These results reflect the sometimes fierce competition among localities to attract large firms, particularly large manufacturing firms. The reduction in child poverty associated with large firms, however, was observed to be significantly smaller during the recession of the early 1990s. This suggests that the development strategy of competing for the relocation of large manufacturing firms is not a comprehensive strategy.

Concentrations of economic activity in other sectors can be a benefit during recessions. Although concentrations in farming and services generally increase child poverty, they reduced it slightly during the recession for which we have data. Farming and services may offer portfolio diversity during recessions. For farming, the effect may be because the economic cycle in agriculture does not correspond exactly to the general business cycle. By contrast, the service sector may be less cyclical than the general economy.

It would be fruitful to confirm the results presented here by examining the recession that began in March 2001 in future research. Also, it would be fruitful to test these results using the more sophisticated measures of economic diversity that have been developed in the literature. Similarly, the exact nature of the effect of large firms could be explored by developing more sophisticated summary measures of the composition of local firms.

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