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IFPRI Discussion Paper 01076

March 2010

Poverty Rate and Government Income Transfers

A Spatial Simultaneous Equations Approach

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PARTNERS AND CONTRIBUTORS

IFPRI gratefully acknowledges the generous unrestricted funding from Australia, Canada, China, Denmark, Finland, France, Germany, India, Ireland, Italy, Japan, the Netherlands, Norway, the Philippines, South Africa, Sweden, Switzerland, the United Kingdom, the United States, and the World Bank.

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ABSTRACT

The poverty rate and income transfer are clearly correlated. However, not much research has attempted to determine the causal linkage between the two. Previous research has primarily focused on the poverty-reducing impact of income transfer. In this paper, we apply a simultaneous equation system of spatial regressions to uncover the spatial pattern of the relationship between the poverty rate and income transfer, using a sample of 3,001 U.S. counties. The results are in line with theoretical expectations; they provide evidence of a significant simultaneity effect between the poverty rate and income transfer. Our findings also confirm the presence of significant spatial autocorrelation. Contrary to previous studies, we find that more generous counties tend to do a better job of reducing poverty and that counties with more poor tend to be less generous, creating incentive for the poor to participate in the labor force. Furthermore, counties located in devolution states perform better in both poverty reduction and income transfer. These findings are missing from extant literature that focuses only on the poverty-reducing impact of welfare payments.

Keywords: poverty, income transfer, spatial econometrics, endogeneity, SHAC

ACKNOWLEDGEMENTS

A previous version of this paper was presented at the IVth World Conference of the Spatial Econometrics Association, Chicago, Illinois, June 9-12, 2010.

1. INTRODUCTION

That income transfer reduces poverty has been a longstanding and lingering debate (O'Neill 1986; Kenworthy 1999; Herzer and Klump 2009). While a considerable amount of research has focused on the poverty-reducing impact of income transfer, the role of the poverty level in the policymaking decision to determine the level of transfer has been largely ignored. Furthermore, the amount counties spent on income transfer across the United States varies considerably. Some counties are spending rather generously, while other counties are maintaining only the required level of spending, despite high and persistent poverty rates and the availability of federal and often state funds. A recent study by Lobao and Kraybill (2009) has elaborately analyzed the impact of poverty on economic development and service provision activities put forth by local governments to boost their communities but failed to account for the effect of income transfer on poverty dynamics. Even more surprising, as of this study, no research has attempted to characterize the interrelationship between poverty and transfer payments. It is clear that the levels of government income transfer vary in response to the level of poverty (Hoynes, Page, and Stevens 2005; Caminada et al. 2010). In this study, we are primarily concerned with the interdependence between the poverty rate and income transfer. It is worth pointing out that the literature is predominantly inconclusive on the potential impact of poverty on income transfer. Some critics contend that high poverty levels may compel local governments to engage in a race to the bottom by trading off between growth and redistributive activities. Others argue that the penalty of poverty may induce communities to be generously liberal when setting up income transfer levels.

To assess these contentions, while at the same time analyzing the interdependence between the poverty rate and income transfer, we apply a simultaneous equation framework in a spatial context. Our method is rooted in the theoretical model of welfare competition among local governments. The empirical implementation draws from recent applications of spatial econometrics in a multi-equation framework by Jeanty, Partridge, and Irwin (2010); Gebremarian et al. (2008); and Boarnet (1994).

The rest of the paper is organized as follows: in Section 2 we present a review of the literature on antipoverty strategies and its application in the United States. Sections 3 and 4 discuss the theoretical framework, empirical specification, and econometric issues. Section 5 describes the data. Section 6 discusses the empirical results, diagnostic tests, and interpretation. Section 7 concludes the paper.

2. LITERATURE REVIEW

To address poverty issues, Drèze and Sen (1991) identify two distinct but interrelated roles for public policy. First is the promotional role, which aims at eliminating chronic poverty by enhancing the asset base of households. Second is the protective role, which aims to prevent those households most vulnerable to adverse shocks from entering into a spiral of poverty. As Norton, Conway, and Foster (2000) put it, the rationale for implementing welfare programs or social safety nets is to promote dynamic, cohesive, stable societies through increased equity and security. Haddad and Zeller (1996) point out that social safety nets are designed to reduce poverty and to protect the income entitlements of particularly vulnerable groups during times of severe stress. Subbarao et al. (1996) define social safety nets as programs to protect a person or household against chronic incapacity to work and a decline in this capacity from a marginal situation that provides a minimal livelihood for survival with few reserves. It follows that social safety net programs should apply to contexts of sudden income or consumption collapse with potentially catastrophic consequences (Devereux 2002). For many households in poverty, such programs are the only hope of a life free from chronic poverty, malnutrition, and disease (Coady 2004). Traditionally, welfare programs are designed to serve two key functions: (1) to transfer resources toward the poorer members of society to bring them out of poverty, and (2) to provide greater opportunities for individuals to mitigate risks from random events.

Safety nets protect individuals from transient periods of poverty as a result of random shocks such as loss of employment, sudden illness, or natural disasters (Besley, Burgess, and Rasul 2003). They also serve to protect individuals from lifetime poverty that can arise from lack of assets such as human capital and physical capital. Hence, social safety nets target three rather heterogeneous groups: (1) the chronic poor, who have limited access to income and instruments to manage risk. For these households, even small reductions in income can have dire consequences; (2) the transient poor, whose income is near the poverty line and may fall into poverty when an individual household or the economy as a whole faces hard times; and (3) those with special circumstances whose vulnerability may stem from disability, discrimination, displacement, "social pathologies" of drug and alcohol abuse, domestic violence, or crime (World Bank 2007). The heterogeneity of poor households determines the nature and design of social safety net programs. In Table 2.1, Devereux (2002) provides an example of correspondence between the nature of poverty and possible antipoverty interventions.

Table 2.1—Poverty determinants and antipoverty interventions

Determinants of poverty	Antipoverty interventions
Low productivity	Income generation schemes
(chronically low returns to labor)	(productivity-enhancing interventions)
Vulnerability	Safety nets
(transitorily low returns to labor)	(direct transfers, productivity-restoring interventions, or consumption-smoothing microfinance)
Dependency	Social welfare
(inability to work)	(direct transfers)

Source: Devereux (2002).

Devereux (2002) argues that low productivity that causes chronic poverty is best addressed through productivity-enhancing interventions such as irrigation programs and rural infrastructure development. In the short term, vulnerability that leads to transient poverty is best addressed through social safety nets such as cash or in-kind transfers. However, dependency cannot be solved by productivity-enhancing interventions; direct transfers toward the poor should be more efficient.

Social safety net programs can take the form of cash transfers such as pensions, child allowances, or unemployment benefits. They can also be in-kind transfers of commodities such as food subsidies, housing subsidies, or energy subsidies. Some variant may provide income indirectly by offering vulnerable groups employment in public works programs or, more broadly, by providing services such as health and education (Besley, Burgess, and Rasul 2003). Incorporating the notion of income volatility and poverty dynamics, Pritchett (2005) argues that income volatility creates the demand not just for transfer programs to those whose incomes are chronically low (safety nets), but also for insurance-like schemes that would pay off not only when income is absolutely low, but also when households experience negative shocks (safety ropes). Thus, while a "safety net" program might be more popular the more effectively it transfers from richer to poorer households, a "safety rope" program might cause little net redistribution but be popular because it serves an important insurance function in transferring resources from good states to bad states. This distinction is crucial in understanding the political economy of welfare programs.

How to design antipoverty schemes has always been a dilemma. Should the government provide poor people with enough income to cover basic needs such as food, shelter, and clothing or instead focus on improving local opportunities that help the poor accumulate more assets? In the United States, while social insurance improves opportunities for poor families, limited public assistance provides support to cover their basic needs.

Antipoverty policy in the United States revolves around the provision of safety nets to bail out socially disadvantaged households in the presence of short-term shocks (Barrett and Swallow 2006). Research on the impact of welfare on poverty rates can be grouped into two categories. In one category are studies contending that welfare decreases poverty by raising the income of the poor above poverty thresholds, and, in another, are those claiming that welfare has no impact on poverty. Peterson and Rom (1989); Osberg (2000); Hoynes, Page, and Stevens (2005); and others find a significant positive correlation between government transfers and changes in the poverty rate. For example, Schoeni and Blank (2000) find evidence that welfare policy changes introduced in 1996 have reduced public assistance participation while increasing family earnings; as a result, poverty declined. Lichter and Jensen (2002) show that since the introduction of the 1996 reform act, rural poverty rates have declined among female-headed families along with the rates of welfare receipts. Moreover, labor force participation has increased as well as average earnings. In a cross-country analysis, Kenworthy (1999) finds that social-welfare policies do help to reduce poverty; however, he points out that the welfare programs in the United States are less effective than those in other industrialized countries.

Moffitt and Rangarajan (1991) provide evidence suggesting that increases in the Aid to Families with Dependent Children (AFDC) program tax rate was not an effective tool for increasing labor supply and work incentives of female heads. Reviewing the Personal Responsibility and Work Opportunity Reconciliation Act , Danziger (2002) concludes that many recipients reach time limits without finding stable jobs even in the presence of favorable economic conditions. Iceland (2003) points out that although the majority of welfare leavers are working, they usually have low-wage jobs so that their earnings remain low. As a result, many remain in poverty for awhile after leaving welfare.

Analyzing the impact of welfare transfers, Fremstad (2004) concludes that

- between 50 to 75 percent of those leaving welfare remain poor two-to-three years after leaving welfare;
- 42 percent of those leaving welfare remain poor for about five years after leaving welfare, compared with 55 percent who are living at the poverty rate in the first year after leaving welfare; and
- the net income of those leaving welfare in the year after they exited welfare is lower than their income prior to leaving.

Using the National Longitudinal Survey of Youth 1979 in the United States (Bureau of Labor Statistics 2008), Ulimwengu (2008) found that, in general, employed individuals who choose not to participate in welfare programs have at least a 50 percent chance of moving out of persistent poverty. By contrast, unemployed individuals have almost no chance of escaping persistent poverty if they choose not to participate in welfare programs. Work disincentive effects for Aid to Families with Dependent Children–Unemployed Parent (AFDC–UP) participants ranged from a loss of 42 to 50 hours per month for husbands and a loss of 29 to 33 hours per month for wives (Hoynes 1996). However, for those not included in the AFDC–UP, most families would still fail to increase earnings sufficiently to replace any resulting loss in income as a result of their lack of participation in the program.

Most of these studies fail to account for geographical spillovers of both poverty and transfer, which may lead to biased estimates and erroneous policy recommendations. In addition, the causal effect of the poverty rate on the level of transfer is often ignored. In the next section, we present a theoretical framework that incorporates geographical spillover across local jurisdictions and cross-correlation between poverty and income transfer. As Lobao and Kraybill (2009) point out, county governments merit consideration in studying the determinants of poverty and appraising the programs and policies that improve well-being across U.S. jurisdictions. Indeed, they found that even poorer communities can take steps to build local capacity, resources, and networks that expand programs for local businesses and low-wage people.

3. ANALYTICAL FRAMEWORK

The focal point of the present model is the essential interdependencies between the poverty rate and income transfer level in a spatial framework. Following Brueckner (2000), the model of welfare competition between jurisdictions can be adapted to derive an explicit spatial simultaneous model for poverty and income transfer. Let us assume that a lump-sum transfer b_i is provided to socially disadvantaged families in jurisdiction i. These poor families work at low-skill jobs, receiving a wage of $w(L_i)$, where L_i represents the poor population in jurisdiction *i* with $\partial w/\partial L_i < 0$. It follows that the poor families receive a gross income of $w(L_i) + b_i \equiv G_i$ in jurisdiction i. In equilibrium, the distribution of the poor population must satisfy the following:

$$w(L_j) + b_j \equiv G, \text{ j} = 1,\ldots,\text{n, and} \tag{1}$$

$$\textstyle\sum_j^n L_j = \bar{L}, \tag{2}$$

where *G* is the endogenous, uniform equilibrium level of gross income across jurisdictions, and $\bar{L}$ is the total number of poor in the economy. Solving (1) and (2) yields solutions for both *G* and L_j, j = 1,…, n, as functions of transfers in all jurisdictions. Explicitly, the optimal number of poor families in jurisdictions *i* is given by

$$L = H(b_i, b_j) \tag{3}$$

where $H_{b_i} > 0$, meaning that jurisdiction *i*'s poor population increases when social transfers in jurisdiction *i* rises.

In jurisdiction i, the individual utility function to be maximized is given by $U = (c_i, G_i, X_i)$ associated with a budget constraint $c_i = g_i - b_i L_i/m$, where m is the uniform number of taxpayers in each jurisdiction, $X_i$is a vector of characteristics of jurisdictions *i* endogenously determined in the model, $c_i$is the level of private consumption, and y_i, the exogenous individual income. Substituting for c_i, G_i, and L_i, the objective function becomes

$$U[g_i - b_i L_i/m\,, w(L_i) + b_i; X_i] = U\{g_i - b_i H(b_i, b_j)/m\,, w[H(b_i, b_j)] + b_i; X_i\} \equiv V(b_i, b_j; X_i). \tag{4}$$

Thus, in choosing the optimal level of transfer b_i^*, jurisdictions account for the inflow of the poor families caused by a higher transfer, which ultimately moderates the incentive for redistribution. Jurisdiction *i* chooses b_i^*, to maximize equation (4) by setting $\partial V/\partial b_i = 0$, which depends on b_j and X_i; thus, the optimal b_i^*will also depend on welfare benefits elsewhere (b_j^*) and on jurisdiction *i*'s characteristics and can be written as

$$b_i = R(b_j; X_i). \tag{5}$$

Substituting equation (5) in (3) yields[1]

$$L = H[R(b_j; X_i); R(b_i; X_j)] = P(L_j; X_i) \tag{6}$$

Equation (6) states that the poor population in jurisdiction *i* depends on poor population in other jurisdictions as well as on jurisdiction *i*'s characteristics.

[1] From equation (3), $b_j = F(L_i, b_i)$, which when substituted in (5) yields $b_i = F(L_i, X_i)$, meaning that the level of transfer depends also on the number of the poor.

Empirical Model and Econometrics Issues

Consistent with the theoretical model developed above, we consider the following system of equations:

$$y_g = Y_g\theta_g + \rho_g W y_g + X_g\beta_g + \varepsilon_g, \text{ with } g = 1,\ldots, M \, , \tag{7}$$

where in the g^{th} equation, y_g is the $n \times 1$ vector of cross-sectional observations on the dependent variable, X_g is an $n \times k$ vector of cross-sectional observations on k exogenous variables, Y_g is a corresponding $n \times L$ matrix of observations on L endogenous variables, ε_g is the $n \times 1$ disturbance vector with zero mean, ρ_g is the spatial autoregressive parameter, W is an $n \times n$ spatial weights matrix of known constants, and θ_g and β_g are regression parameters. The error term ε_g is allowed to be spatially correlated with a spatial structure of unknown form; $\varepsilon_{g,i}$ is expected to be correlated with $\varepsilon_{g,j}$ when the areal units i and j are proximate. The residuals across equations $\varepsilon_{g,i}$ and $\varepsilon_{m,i}$ $(g \neq m)$ may also be correlated. But, we adopt a limited information instrumental variable approach.

Here $M = 2$, where y_1 and y_2 represent 2007 poverty rate and log of 2007 per capita income transfer in a given county, respectively. Reverse the order of these two variables for Y_1 and Y_2. We proceed with a spatial econometrics approach by estimating non-spatial models that are in turn scrutinized for spatial dependence.

To account for spatial autocorrelation in a lattice data analysis, a spatial weights matrix defining the neighborhood structure for each location is required. Unfortunately, theory provides little guidance with respect to choosing the correct weights matrix. We elect to use a first-order queen contiguity spatial weights matrix.[2] Analysis of extant county economic data suggests that neighborhood influences extend out approximately 40–50 miles and then dampen appreciably (Wheeler 2001). Our attempt to create a spatial weights matrix using a 50-mile distance cutoff results in 65 counties, located mostly in the western United States, having no neighbors. However, in the eastern United States, where counties are geographically small, this distance would in some instances pick up second-order neighbors (that is, neighbors of neighbors). As is customary in spatial econometrics analysis, the spatial weights matrix is row-standardized so that $W * i_n = i_n$, where i_n is an $n \times 1$ column vector with elements equal to one.

We first ignore endogeneity due to reverse causality and the presence of a spatially lagged variable by estimating each equation using ordinary least squares (OLS) and assess the presence of spatial autocorrelation using Lagrange multiplier (LM) test statistics for error and lag dependence (Anselin 1988), as well as their robust forms (Anselin 2001). The test results show strong evidence of residual spatial autocorrelation in the form of a spatial lag.

Second, we allow for feedback simultaneity or reverse causality but ignore spatial autoregressive lag simultaneity to estimate the model using standard two-stage least squares techniques (2SLS) (model 2). In this case, poverty rate and income transfer are allowed to be simultaneously determined, where identification of each equation rests on exclusion restrictions. The 2SLS residuals are tested for spatial dependence using the instrumental variable (IV) -Moran's I and IV-Lagrange Multiplier (LM) tests described in Anselin and Kelejian (1997). We also carry out diagnostic tests for endogeneity. Since both sets of tests reject the null hypotheses of no spatial autocorrelation and no endogeneity, a spatially lagged dependent variable is added in each respective equation in addition to the endogenous variable. Each equation is now estimated using spatial S2SLS (Kelejian and Prucha1998; Kelejian and Prucha 2004).

While estimation of the OLS and 2SLS regressions is straightforward, the spatial 2SLS estimation warrants some attention because of the combination of the (non-spatial) endogenous variable and the spatially lagged dependent variable in each equation.

Consider each equation in a compact form for ease of exposition.

[2] In a queen contiguity spatial weights matrix, two locations (i and j) are considered neighbors if they share a common border or a common vertex, in which case $W_{ij}=1$.

$$y_g = Z_g \delta_g + \varepsilon_g \tag{8}$$

where $Z_g = (Wy_g,\ Y_g,\ X_g)$ and $\delta_g' = (\rho_g', \theta_g', \beta_g')$, *g=1,2.*

Spatial Two-Stage Least Squares

Let Q be an $n \times p$ matrix of instruments constructed as a function of *X* and *W.* To allow for the endogenous variables Y_j, in addition to the spatially lagged variable in the *j* equation, we set $X = X_1 \cup X_2$, such that common elements in X_1 and X_2 are included in *X* once. Under the assumption that $|\rho_g| < 1$, Kelejian and Prucha (1998; 2004) show that it is reasonable to take Q to be a subset of the linearly independent columns of $(X, WX, \ldots, W^s X)$.[3]. Other optimal instruments have recently been proposed in Lee (2003) and Kelejian, Prucha, and Yuzefovich (2004). However, Monte Carlo experiments suggest that the overall performances of the estimators using different forms of instruments were very similar, giving preference to the computationally simpler set of instruments.[4]

Define $P = Q(Q'Q)^{-1}Q'$ and $\hat{Z}_g = PZ_g$;, then the spatial two-stage estimator has the following form:

$$\hat{\delta}_{2SLS_g} = (\hat{Z}_g' Z_g)^{-1} \hat{Z}_g' y_g. \tag{9}$$

If the weights matrix in each of the respective spatial lag models underbounds the true spatial interaction in the data, there will be remaining spatial error autocorrelation. Hence, the spatial 2SLS residuals are scrutinized for any remaining spatial error autocorrelation, using the generalized LM test suggested by Anselin and Kelejian (1997). While the transfer equation rejects the null hypothesis of no spatial autocorrelation, the poverty equation does not.

To address the remaining spatial autocorrelation in the transfer equation, we employ the feasible generalized spatial 2SLS estimator (Kelejian and Prucha 1998). We supplement this with the nonparametric spatial heteroskedasticity and autocorrelation consistent (SHAC) estimator of the variance–covariance matrix recently proposed by Kelejian and Prucha (2007).

Using equation (9) as a starting point, the asymptotic distribution of $\hat{\delta}_2 = \hat{\delta}_{2SLS_2}$ involves the variance–covariance matrix: $\Psi = n^{-1} Q' \Sigma Q$, where $\Sigma = (\sigma_{ij}) = E\varepsilon_2 \varepsilon_2'$. Let $\hat{\varepsilon}_2 = y_2 - Z_2 \hat{\delta}_2$ and $\widehat{\Psi}$ be the estimator of Ψ. Kelejian and Prucha (2007) show that the elements *(r, s)* of $\widehat{\Psi}$ are given by

$$\widehat{\Psi}_{(r,s)} = n^{-1} \sum_{i=1}^{n} \sum_{j=1}^{n} q_{ir} q_{js} \hat{\varepsilon}_{2i} \hat{\varepsilon}_{2j} K(d_{ij}/d), \tag{10}$$

where d_{ij} is the distance between county *i* and county *j*, *K*(.) is a kernel function with the usual properties, *d* is the bandwidth, such that $K(d_{ij}/d) = 0$ for $d_{ij} \geq d$. Following Kelejian and Prucha (2007), we focus on the Parzen kernel but experiment with two other kernels, Barlett and Epanechnikov, for a robustness check. The bandwidth is set to 19.59397, 31.26269, and 57.41537 miles, corresponding to 7, 14, and 40 neighbors, respectively.

With $\widehat{\Psi}$ at hand, the HAC variance for $\hat{\delta}_2$ is given by

$$AsyVar(\hat{\delta}_2) = n^2 (\hat{Z}_2' \hat{Z}_2)^{-1} Z_2' Q (Q'Q)^{-1} \widehat{\Psi} (Q'Q)^{-1} Q' Z_2 (\hat{Z}_2' \hat{Z}_2)^{-1}. \tag{11}$$

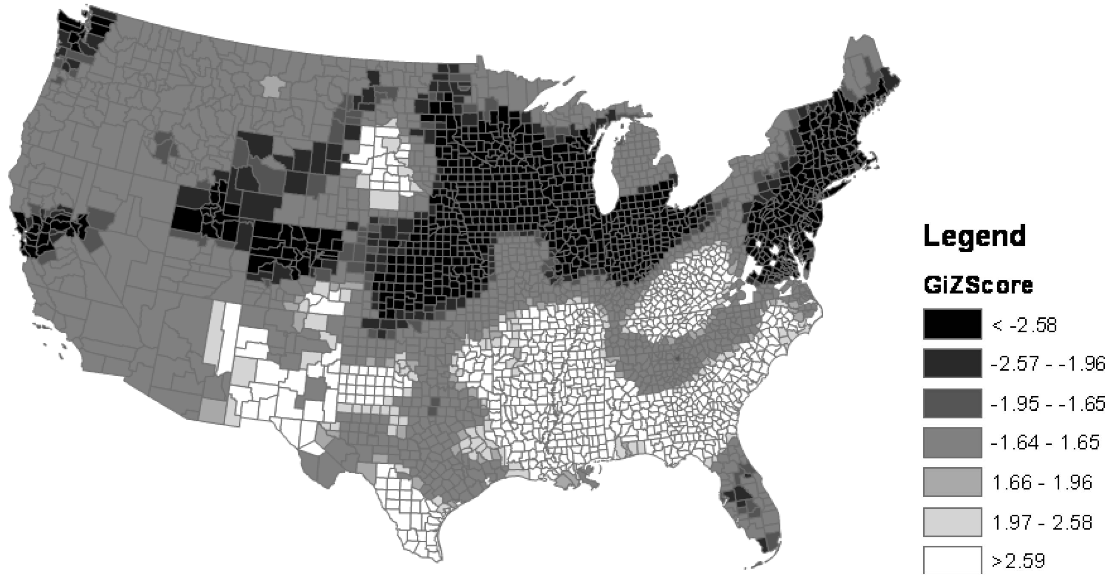
[3] The spatial lag of the constant term is not taken, since doing so would result in a column of ones when *W* is row-standardized. We choose $s = 2$.

[4] Lee's (2003) optimal instruments involving the inverse of an $N \times N$ matrix would be computationally burdensome.

Data Sources and Variables

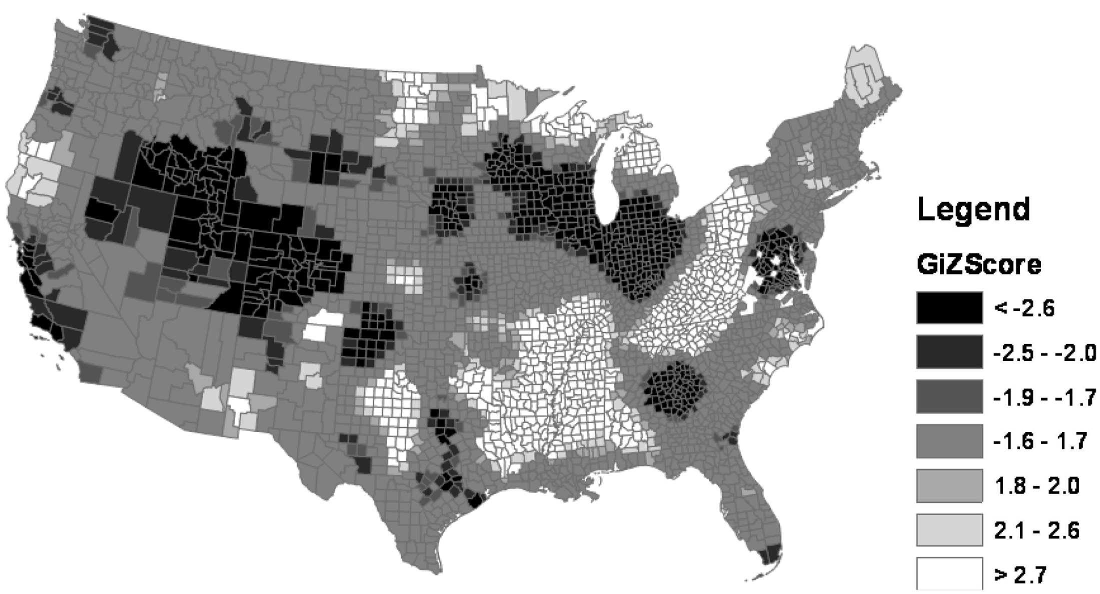
This study uses a sample of 3,001 U.S. counties as units of analysis. To study poverty and particularly income transfers, counties remain the most conceptually relevant units (Isserman, Feser, and Warren 2009 and Peters 2009). As local governments, counties are increasingly recognized as the fastest-growing general purpose governments partly due to devolution (Lobao and Kraybill 2005). Using the Getis-Ord (1996) Z-score, we map the spatial pattern of both poverty rates and income transfer. Figures 3.1 and 3.2 both display significant clusters of poverty. The white spots represent high concentrations of poverty rates and income transfers, while the black spots represent low levels of the two variables.

Figure 3.1—Spatial pattern of poverty in 2007 (Getis-Ord Z-score)



Source: Authors' estimation.

Figure 3.2—Spatial pattern of income transfer in 2007 (Getis-Ord Z-score)



Source: Authors' estimation.

The data are taken from various sources, including the U.S. Census Bureau, the Bureau of Economic Analysis, and the 1997 Census of Governments. Table 3.1 presents the list of variables as they pertain to each equation, variable definitions, and data sources. Extant research on poverty provides a good background when it comes to choosing the control variables in the poverty equation. A recent review of this literature can be found in Peters (2009). We select among the variables that have been unanimously found to affect poverty. First, we include a time-lagged variable, the 1997 poverty rate, to account for potential inertia effects. Allowing for a time lag also helps control for any fixed effects that persist over time.

Second, we include two agglomeration economies variables: log of population density and distance to the nearest metropolitan area. Population density is included to capture any returns to scale that may be present in high density areas. Distance to the nearest metropolitan area controls for the rural–urban and urban–rural spillovers (Partridge and Rickman 2008). We expect a positive distance effect on poverty, based on the assumption that distance decreases labor demand more than it could possibly reduce labor supply, therefore reducing employment and wages. Further, a number of studies point to a spatial mismatch between workers and jobs in poorer and more rural counties, reducing the chance of welfare recipients to find employment (see, for example, Gibbs 2002; Lichter and Jensen 2002). Thus, we anticipated a positive relationship between the poverty rate and distance to the nearest metropolitan area, expecting that fewer work opportunities would lead to higher poverty rates. We include the 2000 county unemployment rate to capture location-specific labor market conditions.

The literature on poverty also points to several demographic traits of counties generally found to influence poverty outcomes. We include both the percent of the population under age 18 and the percent over 64 to control for the proportion of the population out of the labor force. Households headed by single females as a proportion of all households and the percent of adults over 25 with at least a college degree are included to control for populations with low and high earnings, respectively. While the presence of female-headed households is expected to increase poverty, higher education attainment should reduce poverty. These variables take on 2000 values to avoid potential endogeneity. Finally, it is highly recognized that counties located in states devolving welfare programs to local governments gain more control over funds that county officials can apportion to jobs and business attractions in order to combat poverty (Tickamyer et al. 2007). Evidence from state-level studies also suggests that states playing a pioneer role in devolving welfare programs to counties appear to do a better job at creating jobs for their welfare recipients (Rodgers 2005). We include a dummy variable equal to one if the county is located in a state where welfare is devolved to county government and zero otherwise.

Regarding the income transfer equation, as previously mentioned, existing empirical research focusing directly on the determinants of income transfer levels is relatively meager. In line with the theoretical framework used in this paper, this equation is based on the premise that, in setting the optimal level of income transfer, local governments account for the inflow of the poor and the characteristics of their jurisdictions. Thus, we include characteristics of both individuals and jurisdictions to reflect both demand and supply sides.

First, as in the poverty equation, per capita income transfer in 1997 is included to capture inertia or path dependency. Findings by Lobao (2007) and Reese (2006) indicate that counties having a history of providing greater support for the poor will continue to do so. However, to provide income transfer for the disadvantaged groups in their populations, county governments must have the wherewithal to do so. Principally, they must possess adequate and autonomous resources. To capture the county government capacity for providing transfer services, we include per capita local government tax revenue and the ratio of county revenue to state and federal revenue.

Table 3.1—Data sources and variable descriptions

Variable	Description	Poverty equation	Transfer equation	Source
Dependent				
povrt07	Population poverty rate (%), 2007		(+/-)	US Census: SAIPE (Small Area Income and Poverty Estimates)
lpctanf07	Log of per capita TANF[5], 2007	(+/-)		US Census (REIS-BEA[6] 2009)
Independent				
Time lag				
povrt97	Population poverty rate (%), 1997	(+)		US Census
lpctanf97	Log of per capita TANF ($), 1997		(+)	REIS-BEA
Agglomeration				
lpopdens00	Log of population density, 2000	(+/-)		
nearestma	Distance (in km) to the nearest MSA (Metropolitan Statistical Area) as defined in 2000	(+)		Authors' computation
Economic				
lnpcpinc00	Log per capita personal income, 2000		(+/-)	US Census (REIS-BEA)
unemprt00	Unemployment rate (%) in 2000	(+)		U.S. Census Bureau
pctfem_un	Female unemployment rate (%), 2000		(+/-)	
Demographic				
pctu18	Percent of population under 18 years of age (%), 2000	(+/-)		
pct65ov9	Percent of population 65 years or plus (%), 2000	(+/-)		
bsgrad90	Percent of population with a college degree or plus (%), 1990	(-)		U.S. Census Bureau
pffhhu18	Percent % of female-headed family households with children <18 years (%), 2000	(+)		
Capacity				
devola	Dummy=1 if devolution and zero otherwise	(-)	(+)	Lobao and Kraybill 2005
homerule	Categorical: 1=Strong Dillon, 2=Weak Dillon, 3=Weak home rule, and 4=Strong home rule		(+/-)	Salvino 2007
revcap97	From Census of Governments, county general revenue per capita (1,000s), 1997		(+)	1997 Census of Governments
fsown97	From Census of Governments, federal+state revenue/county-own source revenue, 1997		(+/-)	

Source: Authors' compilation.

Second, we include two agglomeration economies variables: log of population density and distance to the nearest metropolitan area. Population density is included to capture any returns to scale that may be present in high density areas. Distance to the nearest metropolitan area controls for the rural–urban and urban–rural spillovers (Partridge and Rickman 2008). We expect a positive distance effect on poverty, based on the assumption that distance decreases labor demand more than it could possibly reduce labor supply, therefore reducing employment and wages. Further, a number of studies point to a spatial mismatch between workers and jobs in poorer and more rural counties, reducing the chance of welfare recipients to find employment (see, for example, Gibbs 2002; Lichter and Jensen 2002). Thus, we

[5] Temporary Assistance for Needy Families.
[6] Regional Economic Information System-Bureau of Economic Analysis.

anticipated a positive relationship between the poverty rate and distance to the nearest metropolitan area, expecting that fewer work opportunities would lead to higher poverty rates. We include the 2000 county unemployment rate to capture location-specific labor market conditions.

The literature on poverty also points to several demographic traits of counties generally found to influence poverty outcomes. We include both the percent of the population under age 18 and the percent over 64 to control for the proportion of the population out of the labor force. Households headed by single females as a proportion of all households and the percent of adults over 25 with at least a college degree are included to control for populations with low and high earnings, respectively. While the presence of female-headed households is expected to increase poverty, higher education attainment should reduce poverty. These variables take on 2000 values to avoid potential endogeneity. Finally, it is highly recognized that counties located in states devolving welfare programs to local governments gain more control over funds that county officials can apportion to jobs and business attractions in order to combat poverty (Tickamyer et al. 2007). Evidence from state-level studies also suggests that states playing a pioneer role in devolving welfare programs to counties appear to do a better job at creating jobs for their welfare recipients (Rodgers 2005). We include a dummy variable equal to one if the county is located in a state where welfare is devolved to county government and zero otherwise.

Regarding the income transfer equation, as previously mentioned, existing empirical research focusing directly on the determinants of income transfer levels is relatively meager. In line with the theoretical framework used in this paper, this equation is based on the premise that, in setting the optimal level of income transfer, local governments account for the inflow of the poor and the characteristics of their jurisdictions. Thus, we include characteristics of both individuals and jurisdictions to reflect both demand and supply sides.

First, as in the poverty equation, per capita income transfer in 1997 is included to capture inertia or path dependency. Findings by Lobao (2007) and Reese (2006) indicate that counties having a history of providing greater support for the poor will continue to do so. However, to provide income transfer for the disadvantaged groups in their populations, county governments must have the wherewithal to do so. Principally, they must possess adequate and autonomous resources. To capture the county government capacity for providing transfer services, we include per capita local government tax revenue and the ratio of county revenue to state and federal revenue.

Two other variables gauge the local governments' ability to provide for its poor: devolution and home rule. Where welfare reform is devolved to counties, county governments have the potential to better serve the poor, if so inclined. Similarly, counties operating under home rule, as opposed to Dillon's rule, have more leeway with respect to implementing more robust policies benefiting their citizens. Geon and Turnbull (2004) find that there is a greater tendency for counties under home rule to behave as if they are constrained to satisfy community demand as depicted by the median voter framework.

Finally, where individuals are less dependent on income transfers, we expect the income transfer levels to be lower. We include per capita personal income to capture this segment of the population. We also include the percent of female unemployment to represent the part of the population with greater per capita dependence on income transfer. Here the effect can be a "race to the bottom" or a "race to the top."

4. ESTIMATION RESULTS

Descriptive statistics and estimation results are presented in Tables 4.1 to 4.4. We start with non-spatial specifications where both OLS and 2SLS residuals are tested for spatial autocorrelation and the null hypothesis of no spatial autocorrelation is rejected for both. Then both equations are estimated using spatial two-stage least squares (S2SLS), whose residuals are also tested for spatial autocorrelation to see whether including a spatial lag in each of the equations purges the residuals from spatial autocorrelation. The null hypothesis is rejected for the transfer equation but not for the poverty equation. We elect to correct for the spatial autocorrelation in the transfer equation using parametric (generalized spatial 2SLS) and nonparametric approaches (SHACs). The nonparametric approach (Table 4.4) yields better and more expected results than the parametric one (Table 4.3). Therefore, the discussion below focuses on the S2SLS estimation of poverty estimation (Table 4.2) and the SHAC estimation of transfer equation (Table 4.4).

Table 4.1—Descriptive statistics

Variable	Mean	Std. error
povrt07	15.18887	6.251597
lpctanf07	3.176876	.8840528
povrt97	15.06138	6.322115
lpctanf97	3.281336	.8313643
lnpcpinc00	10.02023	.2213432
unemprt00	5.789899	2.621266
pctfem_un	5.783556	2.732851
lpopdens00	3.758504	1.58451
nearestma	78.2587	58.4117
pctu18	25.54424	3.128666
pct65ov9	14.96203	4.3163
bsgrad90	13.36804	6.433141
pffhhu18	20.69907	7.100266
Devola	.2732423	.4456985
homerule	2.552816	1.0096
revcap97	.742991	.6058711
fsown97	.3079815	.1833154

Source: Authors' estimation.

Table 4.2—Poverty regression results from OLS, 2SLS, and S2SLS[7]

Variable	OLS	2SLS	S2SLS
spatial lag of povrt07			0.035**
			(0.016)
lpctanf07	-0.007	-0.463***	-0.328***
	(0.055)	(0.077)	(0.075)
povrt97	0.739***	0.744***	0.724***
	(0.017)	(0.017)	(0.015)
lpopdens00	-0.034	0.035	0.024
	(0.053)	(0.055)	(0.046)
nearestma	0.004***	0.005***	0.004***
	(0.001)	(0.001)	(0.001)
unemprt00	0.222***	0.265***	0.255***
	(0.033)	(0.035)	(0.024)
pffhhu18	0.112***	0.120***	0.116***
	(0.013)	(0.014)	(0.009)
pctu18	-0.188***	-0.182***	-0.179***
	(0.024)	(0.025)	(0.017)
pct65ov9	-0.203***	-0.187***	-0.184***
	(0.022)	(0.023)	(0.019)
bsgrad90	-0.069***	-0.072***	-0.068***
	(0.010)	(0.010)	(0.008)
devola	-0.883***	-0.788***	-0.764***
	(0.095)	(0.096)	(0.101)
_cons	8.637***	8.970***	8.324***
	(0.952)	(0.954)	(0.756)
R^2	0.860	0.857	0.861
adj. R^2	0.859	0.856	0.860
N	3001	3001	3001

Source: Authors' estimation.

Notes: Standard errors are in parentheses.

* p < 0.10, ** p < 0.05, *** p < 0.01.

[7] OLS: Ordinary List Squares; 2SLS: Two Stage Least Squares; S2SLS: Spatial Two Stage Least Squares.

Table 4.3—Transfer regression results from OLS, 2SLS, S2SLS, and GS2SLS

Variable	OLS	2SLS	S2SLS	GS2SLS[8]
spatial lag of lpctanf07			0.112***	0.059**
			(0.023)	(0.025)
povrt07	0.003	-0.015***	-0.008**	0.001
	(0.003)	(0.004)	(0.003)	(0.004)
lpctanf97	0.872***	0.894***	0.829***	0.833***
	(0.016)	(0.017)	(0.018)	(0.017)
pctfem_un	-0.024***	-0.007	-0.010**	0.001
	(0.006)	(0.006)	(0.005)	(0.005)
revcap97	0.037**	0.029*	0.028*	0.021
	(0.017)	(0.017)	(0.016)	(0.016)
fsown97	0.268***	0.249***	0.195***	0.025
	(0.059)	(0.060)	(0.057)	(0.061)
lnpcpinc00	0.037	-0.208***	-0.140**	-0.057
	(0.064)	(0.072)	(0.066)	(0.066)
devola	0.056**	0.050*	0.056**	0.094***
	(0.027)	(0.027)	(0.024)	(0.033)
Homerule	-0.017	-0.021*	-0.020**	-0.017
	(0.011)	(0.011)	(0.009)	(0.013)
_cons	-0.045	2.547***	1.645**	0.810
	(0.662)	(0.743)	(0.686)	(0.693)
R^2	0.653	0.647	0.676	0.608
adj. R^2	0.652	0.646	0.675	0.607
N	3001	3001	3001	3001

Source: Authors' estimation.

Notes: Standard errors are in parentheses.
* p < 0.10, ** p < 0.05, *** p < 0.01.

Table 4.4—SHAC standard errors for the spatial 2SLS transfer model

	(1) Neighbors=7		(2) Neighbors=14		(3) Neighbors=40	
Parzen kernel						
wy2_lpctanf07	0.112***	(0.031)	0.112***	(0.031)	0.112***	(0.032)
povrt07	-0.008**	(0.004)	-0.008**	(0.004)	-0.008**	(0.004)
lpctanf97	0.829***	(0.026)	0.829***	(0.026)	0.829***	(0.026)
pctfem_un	-0.010*	(0.006)	-0.010*	(0.006)	-0.010*	(0.006)
revcap97	0.028*	(0.017)	0.028*	(0.017)	0.028	(0.018)
fsown97	0.195***	(0.058)	0.195***	(0.059)	0.195***	(0.064)
lnpcpinc00	-0.140**	(0.069)	-0.140**	(0.070)	-0.140*	(0.074)
devola	0.056**	(0.026)	0.056**	(0.027)	0.056*	(0.030)
homerule	-0.020*	(0.010)	-0.020*	(0.011)	-0.020	(0.013)
Const	1.645**	(0.719)	1.645**	(0.723)	1.645**	(0.770)

[8] GS2SLS: Generalized Spatial Two Stage Least Squares.

Table 4.4—Continued

	(1) Neighbors=7		(2) Neighbors=14		(3) Neighbors=40	
Barlett kernel						
wy2_lpctanf07	0.112***	(0.031)	0.112***	(0.031)	0.112***	(0.034)
povrt07	-0.008**	(0.004)	-0.008**	(0.004)	-0.008**	(0.004)
lpctanf97	0.829***	(0.026)	0.829***	(0.026)	0.829***	(0.027)
pctfem_un	-0.010*	(0.006)	-0.010*	(0.006)	-0.010	(0.006)
revcap97	0.028*	(0.017)	0.028	(0.017)	0.028	(0.020)
fsown97	0.195***	(0.059)	0.195***	(0.061)	0.195***	(0.071)
lnpcpinc00	-0.140**	(0.069)	-0.140*	(0.072)	-0.140*	(0.078)
devola	0.056**	(0.026)	0.056**	(0.028)	0.056*	(0.034)
homerule	-0.020*	(0.011)	-0.020*	(0.012)	-0.020	(0.016)
Const	1.645**	(0.718)	1.645**	(0.746)	1.645**	(0.813)
Epanechnikov kernel						
wy2_lpctanf07	0.112***	(0.031)	0.112***	(0.031)	0.112***	(0.035)
povrt07	-0.008**	(0.004)	-0.008**	(0.004)	-0.008*	(0.004)
lpctanf97	0.829***	(0.026)	0.829***	(0.026)	0.829***	(0.028)
pctfem_un	-0.010*	(0.006)	-0.010*	(0.006)	-0.010	(0.007)
revcap97	0.028*	(0.017)	0.028	(0.018)	0.028	(0.021)
fsown97	0.195***	(0.059)	0.195***	(0.063)	0.195**	(0.077)
lnpcpinc00	-0.140**	(0.069)	-0.140*	(0.074)	-0.140*	(0.083)
devola	0.056**	(0.027)	0.056*	(0.029)	0.056	(0.038)
Homerule	-0.020*	(0.011)	-0.020	(0.013)	-0.020	(0.018)
Const	1.645**	(0.717)	1.645**	(0.765)	1.645*	(0.857)
N	3001		3001		3001	

Source: Authors' estimation.

Notes: Standard errors are in parentheses.
* $p < .10$, ** $p < 0.05$, *** $p < 0.01$.

Overall, the results confirm the presence of positive and significant geographical spillovers in both the poverty rate and the income transfer; on average, the county's poverty rate increases by 0.04 percent when neighboring counties' poverty rates increase by 1.00 percent. This implies the existence of poverty clustering (see Figures 3.1 and 3.2), where counties with similar poverty rates share the same poverty dynamics. A recent study by Peters (2009) identifies 12 statistically distinct poverty clusters in the United States. Our results also confirm previous findings (Peterson and Rom 1989; Kenworthy 1999 Osberg 2000; Lichter and Jensen 2002 and Hoynes, Page, and Stevens 2005) that income transfer does reduce the poverty rate. The initial condition with respect to the poverty rate matters; the 1997 poverty rate significantly affects poverty in 2007, suggesting poverty persistence over the years as reported by Cook and Mizer (1994) and Joliffe (2004).

As shown in previous studies (for example, Ulimwengu 2008; Ulimwengu and Kraybill 2004), unemployment has a significant poverty-increasing effect; our results suggest that a marginal change in unemployment is expected to induce a change of 0.26 in the poverty rate. A similar result is observed for a change in the percentage of female-headed families with children under 18, which has a significant positive effect on the poverty rate. As expected, county remoteness as measured by the distance to the nearest Metropolitan Statistical Area (MSA) has a significant effect on poverty; we find that remoteness from an urban center is a significant contributing factor to the county's poverty status. In their survey, Weber et al. (2005) conclude that poverty is higher and more persistent in the more remote rural counties.

We also find that the stock of human capital, measured here by the percent of population with a college degree or more, is negatively correlated with the poverty rate. Lobao and Kraybill (2009) point out that counties with higher poverty rates have a less educated population. At the household level, Ulimwengu (2009) found that education is critical in preventing entry into persistent poverty. Indeed, those with college degrees are less likely to fall into persistent poverty than those with high school or middle school diplomas.

Counties in states that have gone through devolution have experienced lower poverty rates than other counties. On the one hand, as shown by Tickamyer et al. (2007), counties located in states devolving welfare programs to local governments have substantial resources to combat poverty. On the other hand, higher poverty counties report greater pressure from devolution and rising service demands (Lobao and Kraybill 2009).

Findings on income transfer are consistent regardless of the number of neighbors or the nature of the kernel approximation used. Although negligible, the impact of the poverty rate on per capita income transfer is significant and negative. This suggests that an increase in the number of the poor does reduce the amount of transfer available to each poor person.

Using a non-spatial model, Lobao and Kraybill (2009) found no support for the view that poverty hastens a race to the bottom. To the contrary, our results do provide evidence of a race to the bottom among counties. We find that a 1.00 percent change in per capita income transfer in neighboring counties leads to a 0.11 percent change in per capita income transfer. In other words, in defining its antipoverty strategy, each county seems to pay close attention to what is happening in neighboring counties.

We also find significant inertia or path dependence in the level of income transfer, which confirms the finding by Lobao and Kraybill (2009) that past use of strategies strongly influences future use. Our results show that the 2007 per capita income transfer is significantly and positively correlated with the 1997 per capita income transfer. Similarly, the higher the county's 1997 general income per capita, the higher its 2007 per capita transfer. The same result is observed for the ratio of federal and state funds to a county's own resources.

Similar to the poverty rate, the percentage of women unemployed, which represents a significant share of the poor, tends to reduce the amount of money transferred to each poor person. A1.00 percent increase in personal income is expected to reduce per capita income transfer by 0.14 percent. With respect to the home rule variable, we find that counties operating under home rule set a lower level of income transfer, a result counter to intuition. Devolution counties are found to be more generous than non-devolution counties. This may explain why devolution counties experience lower poverty rates.

5. CONCLUDING REMARKS

The link between government transfers and poverty reduction has been the subject of numerous studies. Surprisingly enough, most of these studies failed to account for geographical spillover of both the poverty rate and government transfers leading to biased estimates and ultimately to erroneous policy recommendations. Moreover, the role of the poverty level in shaping the level of transfer payments has been largely ignored. Our findings are in line with theoretical expectations and underscore the importance of accounting for feedback simultaneity and spatial autocorrelation. Contrary to previous research, focusing on the poverty-reducing impact of income transfer at the state level, which ignores endogeneity and spatial spillovers, we find that more generous counties tend to do a better job at reducing poverty and that counties with more poor tend to be less generous, which may create incentive for the poor to participate in the labor force.

Overall, the results confirm the presence of significant geographical spillovers in both poverty rate and income transfer. Our results also confirm that income transfer does reduce the poverty rate. Although negligible, the impact of the poverty rate on per capita income transfer is significant and negative. We also find evidence of inertia in both the poverty rate and income transfer. Our results provide evidence of a race to the bottom between counties with respect to income transfer.

These findings call for a regional or community approach in the fight against poverty. Indeed, a common policy agenda is likely to move the welfare equilibrium toward the first best solution whenever independent actions generate spillovers. In the presence of cross-county spillovers, efficiency requires that jurisdictions agree on policy coordination as opposed to the option of breaking ranks. The Workforce Innovation in Regional Economic Development (WIRED) initiative, which stresses the critical role talent development plays in creating effective regional economic development strategies, is a perfect example of such a common agenda.

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