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Neighborhood structure and foster care entry risk: The role of spatial scale in defining neighborhoods

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ABSTRACT

The renewed popularity of neighborhood-based child welfare services has been built on studies showing that certain neighborhood demographic characteristics are linked to child maltreatment. In response to this data, public child welfare system reform efforts seek to target services to neighborhoods at high risk for child welfare involvement. This study examines whether or not those neighborhood attributes are related to the risk of entering foster care. These relationships are examined at three spatial scales to establish whether the associations change depending on neighborhood operationalization. Foster care entries between 2000 and 2003 ($n=3311$) from a largely urban California county are geocoded to each of the three scales ($N=46$ zip codes, 320 Census tracts and 983 Census block groups). Fourteen demographic Census indicators are reduced to four meaningful constructs. *Residential instability*, *impoverishment* and *childcare burden* are positively associated with high foster care entry rates no matter how neighborhoods are delineated.

1. Introduction

The ecological perspective has always been present, to a greater or lesser degree in approaches to social problems. Over a half century ago, Shaw and McKay (1942) used maps to identify concentrations of juvenile delinquency in neighborhoods and related this to levels of social organization. Even further back, the establishment of settlement houses in impoverished neighborhoods reflected a recognition that social problems tended to form in particular places (Tratner, 1994). A substantial body of research in the last three decades has put forth considerable evidence that neighborhood characteristics such as rates of impoverishment, childcare burden, residential instability, and minority residents are linked to child maltreatment (see Freisthler, Merritt, & LaScala, 2006 for a review). Ethnographic evidence suggests that residents of African American or low-income neighborhoods may combat the risks of such neighborhood conditions by drawing on the supports of nearby kin and informal social networks. Such networks may facilitate the sharing of information about resources that may be used to help families protect and supervise children (Garbarino & Kostelny, 1992; Korbin, Coulton, Chard, Platt-Houston, & Su, 1998).

These findings about the risks and protective factors of neighborhoods have contributed to a growing movement to apply the ecological perspective to the delivery of public child welfare services. Neighborhoods with high maltreatment rates are frequently the same neighborhoods that have high levels of poverty and other stressful conditions. However, less is known about the degree to which neighborhood social environment impacts the use of foster care in neighborhoods. Employing Coleman's (1988) social capital theory, social resources and networks present in a community may provide supports for parents such as high-quality childcare and other institutional supports (Brooks-Gunn, Duncan, & Aber, 1997). Neighborhoods without such resources might respond to maltreatment by relying more heavily on the formal system of foster care to handle the problem when the informal help of family or friends, or the availability or knowledge about community resources is low. In 2006 in California, 37% of substantiated maltreatment referrals resulted in placement (Needell et al., 2008). For child welfare systems seeking to bring better balance to the provision of out-of-home care and other services to families, understanding how neighborhood attributes are related to placement risk is an important next step.

States and localities that have adopted the neighborhood-based strategy reason that even the most challenging neighborhoods possess resources and strengths that can help families protect children, and with public supports, lead to fewer foster care entries, reentries and shorter spells in out-of-home care (Annie E. Casey Foundation, 2001). For instance, the Annie E. Casey Foundation's Family to Family Initiative supports 17 states and nearly 80 individual sites that commit to child welfare reform, including strengthening neighborhood and kinship supports (Annie E. Casey Foundation, 2007). Child welfare systems participating in community-based initiatives recognize the need to estimate which neighborhoods will need the most foster care so that they can generate foster homes, preventive and other accessible services in and near those areas.

1.1. Spatial scale

Accurate measurement of the impact of the neighborhood environment on risks for children requires explicit attention to how neighborhoods are conceptualized. Most studies of neighborhood effects on

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child maltreatment and subsequent policies promoting community-based interventions have not considered the unique statistical biases that often arise in models that use geographic data (see Coulton, 2005 and Freisthler et al., 2006 for reviews). Neighborhoods are difficult to define discreetly and researchers usually use administrative units of analysis that lack substantive meaning – like Census tracts – as proxies for neighborhoods. Ecological research tends to uses units much larger than true neighborhoods as residents would define them, which downwardly biases estimates of neighborhood effects (Coulton, 2005). Therefore, the way neighborhoods are geographically defined matters when estimating relationships between social need and the risk of an event in an area, such as foster care entry rates in neighborhoods. Yet in the research literature on neighborhoods and child maltreatment various geographies have been used to operationalize neighborhoods.

Census tracts are commonly used because they are convenient (Coulton, Korbin, Su, & Chow, 1995; Deccio, Horner, & Wilson, 1994; Ernst, 2001; Freisthler, 2004; Garbarino & Kostelny, 1992; Garbarino & Sherman, 1980; Zuravin, 1986). Tracts are readily available through the U.S. Census; they are small enough to ensure adequate variability among their demographic characteristics across the study area, yet large enough to ensure stable population sizes of roughly 3000 to 5000 (Sampson, 1999). Others use Census block groups (Coulton, Korbin, & Su, 1999; Young & Gately, 1988), which are a subset of tracts and may better represent what residents consider their neighborhood (Coulton, Korbin, Chan, & Su, 2001). However, address-level information is required to locate maltreatment incidents within Census tracts or Census block groups. Counties are used when maltreatment data are not available or are not reliable at the neighborhood level (Albert & Barth, 1996; Fryer & Miyoshi, 1995; Spearly & Lauderdale, 1983) or zip codes are used when that level of information is available (Drake & Pandey, 1996; Freisthler, Gruenwald, Remer, Lery, & Needell, 2007).

If neighborhoods are unequal along characteristics associated with foster care entry, the accuracy with which these differences are measured is crucial to making good child welfare policy decisions. To that end, the current study addresses the following two-pronged question: How does socioeconomic neighborhood structure affect foster care entry rates and does it depend on the administrative unit used to represent neighborhood? It is expected that entry rates will be higher in places that are more disadvantaged, and that the strength of the association will change depending on spatial scale (Anselin, 2002).

2. Method

2.1. Population

This study examines all 2000 through 2003 first entries to out-of-home care (including relative and congregate care) from Alameda County in California that lasted longer than four days (n=3311) and compares zip codes, Census tracts and Census block groups as proxies for neighborhoods. Limiting the population to first-time entries eliminates the problem of over-representing those children who reenter foster care repeatedly over the years of study. In 2003, only 16% of children with maltreatment referrals in Alameda County had their reports substantiated, and just under two-thirds of these entered child welfare supervised foster care (Needell et al., 2008).

Counties are the administrative jurisdictions for child welfare agencies in California. Alameda County represents variation among foster care incidence rates, poverty levels, and ethnic distributions. During the period of study, roughly 360,000 children lived in this county of approximately 1.4 million residents.[1] In 2000, 1005 children were admitted to foster care for the first time. This number rose to 1033 in 2001 but dropped to 860 in 2002 and 841 in 2003. The corresponding admission rate rose slightly from 2.8 per thousand in 2000 to 2.9 per thousand in 2001 and then fell to 2.4 in 2002 and 2.3 per thousand in 2003 (Needell et al., 2005). According to the 2000 Census, whites make up the largest racial/ethnic group in the county at 49%, followed by Asians at 20%, Hispanics at 19% and African Americans at 15%. The median family income in 2000 was $65,857 and 3% of the County's children were living in poverty.[2]

2.2. Area definitions

By conducting analyses at more than one scale, this study minimizes the tendency to commit the ecological fallacy, whereby conclusions are drawn about smaller units or individuals based on results from aggregated areas. Two of the 48 Alameda County zip codes are dropped from the analysis because they are administrative post office codes and therefore do not have population data or a physical location. One of the 321 census tracts and 12 of the 983 block groups were removed from the analysis because they had zero child population and therefore no risk of foster care entry. At the block group level, the distribution is left-skewed because such small areas contain relatively few people and foster care entries are particularly infrequent at this scale. Thirty-one percent of block groups had no entries and 41% had between one and five entries over the four-year study period. At each spatial scale, adjacent neighborhoods are defined as units that share a boundary.

2.3. Measures

2.3.1. Foster care entry rates

The removal addresses of children entering foster care were geocoded using ArcGIS 8.3 software. Overall, 94% of all removal addresses were assigned a geographic location. The GIS assigns each address an X and Y coordinate that is then associated with a zip code, census tract and block group. Rates of first entries to foster care are calculated for each geographic scale as the number of children living in a given area (zip code, census tract, or block group) entering foster care for the first time in a given year, divided by the total number of children under the age of 18 living in that area, multiplied by 1000. Entry rates within individual geographic units do not have any absolute meaning in this study because the numerator (total entries) is summed across years, while the denominator (child population) is calculated using only Census 2000 figures. Child population data after 2000 are not available at the block group level, so 2000 data was chosen to standardize the denominator across the three spatial scales. Therefore, the raw entry rates are inflated and are not shown here. The purpose of the rates is to establish relative meaning among the geographic scales, with respect to the relationship between entry rates and neighborhood structure.

The data were drawn from the first quarter, 2004 extract of California's Child Welfare Services Case Management System. Under the terms of an interagency agreement with the California Department of Social Services, quarterly extracts from this system are housed at the Center for Social Services Research at the University of California at Berkeley and constitutes the California Children's Services Archive. Administrative data may underestimate the occurrence of abuse and neglect because it is limited to reported maltreatment incidents and is subject to data quality issues, but it is generally accepted as a reliable source of maltreatment information, as well as being the only source of foster care admissions data (Barth, Locklin-Brown, Cuccaro-Alamin, & Needell, 2002).

Using the Coulton et al. (1995) neighborhood child maltreatment study as a guide, a factor model with varimax rotation is constructed at each scale in order to reduce the data, handle multicollinearity, and build constructs that represent neighborhood social structure. Coulton et al. found that a host of social indicators from the 1990 U.S. Census grouped to form constructs. The *Residential instability* construct includes the percent of residents who moved between 1995 and 2000, the percent of

[1] Child population data are from Census 2000, Summary File 2 as projected by Claritas, Inc.

[2] Census 2000 Summary File 3.

Table 1
Descriptive statistics for variables by spatial scale

	Zip codes, $n=46$				Census tracts, $n=320$				Block groups, $n=983$			
	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.
Foster care entry rate[a]	10.3	8.8	0.0	35.0	17.6	80.3	0.0	1,200.0	12.7	47.7	0.0	1200.0
Child population/miles squared[b]	1421.1	1083.6	8.0	5240.9	1413.2	1224.1	3.9	8281.8	1676.3	1410.0	0.0	12,236.9
Residential instability[c]												
% persons who moved between 1995 and 2000	48.7	8.8	21.7	79.2	49.4	12.3	24.1	98.3	47.6	14.5	0.0	100.0
% households in current residence <10 years	66.5	8.5	42.7	84.7	66.4	12.8	30.0	74.4	64.4	15.8	0.0	100.0
% households that moved between 1999 and 2000	19.4	5.2	7.5	34.3	19.8	8.9	0.0	71.4	18.4	10.2	0.0	73.3
Ratio adult males (≥21 years)/adult females (≥ (≥21 years)	0.9	0.1	0.8	1.2	0.9	0.2	0.6	3.5	0.9	0.2	0.0	3.5
% adults ≥65 years	10.8	3.7	4.2	19.6	10.7	5.1	0.0	41.9	11.1	6.9	0.0	73.7
Impoverishment[c]												
% female female-headed families with children	10.8	6.0	2.4	24.3	11.2	8.2	0.0	51.2	11.3	9.8	0.0	56.4
% persons living in poverty	11.9	10.0	2.3	47.5	12.2	11.1	0.0	62.1	11.8	11.6	0.0	75.1
% unemployed residents	3.5	1.7	0.8	8.1	3.7	2.5	0.0	15.7	3.8	3.1	0.0	29.9
% vacant housing units	12.8	4.2	3.7	25.0	13.0	7.3	0.0	37.5	12.9	14.3	0.0	100.0
% African-American residents	15.7	17.1	0.0	58.9	16.9	20.3	0.0	84.3	17.0	21.2	0.0	100.0
Ratio children (0–12 years)/adults(≥21 years)	0.2	0.1	0.0	0.5	0.3	0.1	0.0	0.5	0.3	0.1	0.0	0.8
Immigrant concentration[c]												
% Hispanic residents	15.8	11.0	3.6	49.3	17.9	14.2	0.4	81.4	18.5	15.8	0.0	89.3
% Asian residents	11.9	12.2	3.3	53.9	19.1	15.5	0.0	92.8	18.2	15.9	0.0	93.7
% residents foreign born	25.0	10.2	4.0	48.5	25.7	13.2	0.0	82.8	25.2	14.1	0.0	83.1

[a] Source: California Children's Services Archive, CWS/CMS 2004 quarter 1 extract. Based on the first placement episode of five days or more even if it is not the first actual episode.
[b] Population source: 2000–2003 Claritas Inc. population projections based on the 2000 U.S. Census.
[c] Source: 2000 U.S. Census.

household in current residence for less than 10 years, the percent of households that moved between 1999 and 2000, the ratio of adult males (≥21 years) to adult females (≥21 years) and the percent of people over age 65. *Impoverishment* includes the percent of female-headed families with children, the percent of people living in poverty, the percent unemployed, the percent vacant housing units, the percent African American and the ratio of children (ages 0–12) to adults (ages ≥21). *Immigrant concentration* includes the percent Hispanic, the percent Asian and the percent foreign-born residents. In addition, the analysis includes child population density as measured by the number of children per square mile. Table 1 shows the mean, standard deviation, minimum and maximum for the measures.

2.4. Analytical procedures

Unit independence is required for ordinary least squares regression, but this assumption is often not met in ecological studies because ecological attributes like impoverishment, residential instability and childcare burden do not cluster neatly according to administrative boundaries. As a result, contiguous administrative units may not be distinct or independent with respect to these characteristics. Since the variance of a variable decreases as the unit of analysis becomes larger, the variance–covariance matrix values also change when data are aggregated, such as from block group to census tract (Wong, 1996). Moran's *I* statistic (Moran, 1950) is used to measure spatial autocorrelation and test the hypothesis that the strength of the correlation (along the variables of interest) depends on the spatial scale. Bounded approximately by −1 and 1, Moran's *I* is positive when nearby areas have similar rates (i.e., positive spatial autocorrelation). Moran's *I* is negative when nearby areas have dissimilar rates (i.e., negative spatial autocorrelation).

The univariate Moran statistic represents the level of spatial autocorrelation in each variable by itself. Table 2 compares univariate and bivariate spatial autocorrelation across scales, using the same first order contiguity weights and rook's criteria, which refers to polygons

Table 2
Spatial autocorrelation across scales

	Zip codes ($n=46$)		Census tracts ($n=320$)		Block groups ($n=971$)	
	Univariate Moran's *I*	Bivariate Moran's *I*	Univariate Moran's *I*	Bivariate Moran's *I*	Univariate Moran's *I*	Bivariate Moran's *I*
Foster care entry rate	.34**	–	.18**	–	.18**	–
Child population/miles squared	.29**	.28**	.50**	.03	.59**	.02
Residential instability	.16*	<−.04	.36**	.16**	.40**	.11**
% persons who moved between 1995 and 2000	.10	.10	.33**	.15**	.31**	.10**
% households in current residence <10 years	.16*	.14	.32**	.11**	.38**	.09**
% households that moved between 1999 and 2000	.10	.05	.35**	.14**	.27**	.09**
Ratio adult males (≥21 years)/adult females (≥21 years)	.19*	.18*	.16**	.22**	.14**	.12**
% adults ≥65 years	.27**	.16*	.30**	.03	.25**	<−.01
Impoverishment	.62**	.43**	.69**	.06	.69**	.08**
% female female-headed families with children	.48**	.40**	.56**	.03	.48**	.09**
% persons living in poverty	.38**	.29**	.66**	.12**	.68**	.14**
% unemployed residents	.40**	.32**	.53**	.04	.40**	.07**
% vacant housing units	.28**	−.21	.13**	−.03	.03	−.02
% African-American residents	.49**	.36**	.78**	.07*	.82**	.12**
Childcare burden	.49**	−.15*	.57**	−.05	.54**	−.01
% Hispanic residents	.34**	.04	.65**	<−.01	.68**	−.03
Ratio children (0–12 years)/adults(≥21 years)	.56**	−.04	.57**	−.03	.51**	<.01
Immigrant concentration	.32**	.10	.59**	.06	.62**	<.01
% Asian residents	.24**	<−.01	.63**	.07*	.65**	<.01
% residents foreign born	.41**	.07	.62**	.05	.64**	.03

*$p<.05$; **$p<.01$.

that share a border but not a vertex. Variables are listed in the order that they loaded onto the four factors in the factor analysis. The bivariate Moran statistic measures the relationship between the values of each independent variable at each location and the average values of entry incidence at neighboring locations (lagged *Y*) (Anselin, 2005). Significant positive statistics indicate spatial clustering.

It is hypothesized that the spatial scale will impact the degree of spatial autocorrelation and correlated error in the residuals, which will in turn affect the parameter estimates of how neighborhood socioeconomic characteristics affect entry rates. The statistical model will diagnose and control for this spatial autocorrelation. A linear regression is specified and estimated using OLS for each spatial scale. Each model is weighted by the square root of the child population of each neighborhood in order to control for heteroskedasticity that occurs when the same weight is given to areas with varying population sizes (Greene, 2003). Areas with very few children receive less weight than more densely populated areas. The level of spatial autocorrelation among each of the three neighborhood scales and will be represented by ρ. If significant spatial autocorrelation is present, a GLS spatial lag regression model will take the following form (Bailey & Gatrell, 1995):

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \rho\mathbf{W}\boldsymbol{U} + \boldsymbol{\varepsilon} \tag{1}$$

where **Y** is the outcome variable of the rate of first entries to foster care, **X** is the $n \times p$ matrix of independent variables of neighborhood characteristics, and β is the coefficient for each independent variable. ρ is the spatial autocorrelation coefficient, **W** is a proximity matrix defining neighbors as units that share a common border, $\boldsymbol{U}$ is a zero-mean vector of errors with a variance–covariance matrix **C**, and $\boldsymbol{\varepsilon}$ represents a vector of independent random errors with constant variance. The presence of significant spatial autocorrelation at any spatial scale, as measured by Moran's *I* indicates that the assumption of unit independence has not been satisfied and an OLS regression is insufficient to estimate the relationship between the neighborhood social structure and foster care entry risk. Otherwise, an OLS model is suitable.

3. Results

The factor analysis revealed four principal factors at each spatial scale, which were confirmed by the condition indices. These four factors — impoverishment, residential instability, childcare burden and immigrant concentration explained 82% of the variance in the zip code model, 72% in the tract model, and 66% in the block group model.

3.1. Exploratory spatial data analysis

3.1.1. Zip codes

The univariate statistics for zip codes show a high degree of spatial autocorrelation in the dataset, with all but two predictors significant (the percentage of persons who moved between 1995 and 2000 and between 1999 and 2000). For instance, the significant Moran statistic for foster care entry rates suggests that the pattern of foster care entry across the county is not random, but rather spatially correlated. This can be expected when the units of analysis are not delineated according to demographic homogeneity; socioeconomic characteristics are unlikely to follow zip code boundaries. The univariate Moran statistic is a descriptive indicator of the presence of spatial autocorrelation in the dependent variable and further testing will determine if the census tracts are significantly correlated such that it must be controlled in the regression model.

Foster care entry incidence in one neighborhood is related to several variables at neighboring locations as evidenced by Table 2. Most notably, impoverishment and all the predictors making up this factor except for the percentage of vacant housing units was significant, meaning that highly impoverished neighborhoods tend to be adjacent to neighborhoods with high foster care entry rates.

3.1.2. Census tracts

Similar to the zip code level, Census tracts exhibit foster care entry incidence in one neighborhood related to several variables at neighboring locations. Most of the impoverishment variables are no longer significant at the bivariate level (except for percent poverty), but all of the residential instability components except for percent elderly continue to exhibit spatial autocorrelation. This indicates that when neighborhoods are delineated as Census tracts, residentially unstable areas tend to border areas with high entry rates. Overall, the univariate coefficients tend to be larger in tracts than in zip codes, while the bivariate coefficients tend to be somewhat smaller.

3.1.3. Block groups

Spatial dependence is generally even stronger at this level of aggregation, with all but one variable being highly significant at the univariate level and the majority of the variables remaining significant at the bivariate level. Spatial autocorrelation among most of the predictors generally increases as scale decreases. For instance, the clustering of Asian, Hispanic and African-American residents increases as the neighborhoods get smaller. Three variables that make up the instability factor – percent of residents who moved in the last one, five and ten years – are much less spatially correlated among zip codes than at the other two scales.

3.2. Regression analysis

3.2.1. Zip codes

Table 3 gives the OLS regression model using the four factors from the factor analysis, child population density, and results from initial tests for spatial autocorrelation for all three spatial scales. For zip codes, the overall model accounts for about 69% of the variance. There is no evidence of multicollinearity, non-normality or heteroskedasticity at this scale. Residential instability, impoverishment and childcare burden are significantly positively related to increased risk of neighborhood rates of foster care entry. The Moran's *I* coefficient (.18) indicates significant spatial pattern in the residuals that is unaccounted for by the OLS model. However, the Lagrange Multiplier test of spatial autocorrelation (Anselin, 1988) is more powerful than Moran's *I* against alternatives to spatial autocorrelation and is not significant. Therefore, the OLS model is sufficient for zip codes and there is no need to proceed to a spatial model.

Table 3
OLS and spatial regression models of foster care entry rates and neighborhood social structure at three scales

	Foster care entry per 1000 children					
	Zip codes (n=46)		Census tracts (n=318)		Block groups (n=969)	
	OLS		Spatial lag		Spatial lag	
Variable	*b*	SE	*b*	SE	*b*	SE
Lagged foster care entry			0.23	0.07**	0.17	0.04***
Constant	776.55	82.73***	243.17	32.34**	158.52	13.32***
Residential instability	1.93	0.89*	1.36	0.50**	2.11	0.38***
Impoverishment	5.66	0.76***	4.53	0.60***	4.7	0.43***
Childcare burden	2.13	0.69**	1.51	0.57**	2.16	0.46***
Immigrant concentration	0.7	0.66	−0.53	0.43	−0.61	0.35
Child population per square mile	<−0.01	<0.01	<0.01	<0.01	<−0.01	<0.01
Diagnostics for spatial dependence						
Spatial autocorrelation	0.18**					
Lagrange Multiplier	3.39					
Likelihood ratio	−331.46		10.55**		16.19***	
Adjusted R-squared	0.69					

*$p<.05$, **$p<.01$, ***$p<.001$.

3.2.2. Census tracts

At this scale, two observations are removed because they have child populations fewer than five, which would create unstable rates. The tract-level model accounts for about 40% of the variability in entry rates across the county. Like the zip code model, the four factors are all positively related to foster care entry rates (Table 3). Unlike the zip code model, however, a significant Moran's I (.10, $p<.01$) is supported by a significant Lagrange Multiplier statistic (11.83, $p<.001$). Therefore, a spatial lag model is appropriate and will improve upon the OLS model by controlling the spatial autocorrelation. The spatial autoregressive coefficient (spatially lagged Y) is .23 and is significant ($p<.01$). This spatially lagged foster care entry rate assigns some of the model's explanatory power to levels of the covariates in neighboring census tracts. The likelihood ratio test is significant, indicating that the spatial lag model is a better fit than an OLS model and confirming the significance of the spatial autoregressive coefficient.

3.2.3. Block groups

Two block group observations are removed because fewer than five children lived there.[3] Twelve additional observations are removed because they have zero child population; no children are at risk for foster care entry in these areas. Table 3 gives the spatial lag regression model for block groups. When neighborhoods are further disaggregated into block groups, all covariates except immigrant concentration are significant. The significant Moran's I (.06, $p<.01$), Lagrange Multiplier (17.95, $p<.001$) and the likelihood ratio tests (16.19, $p<.001$) point to the appropriateness of a spatial lag model. As in the tract-level analysis, the significant spatially lagged entry rate (.17, $p<.001$) attributes some of the model's effects to levels of the covariates in contiguous block groups. Substantively, residential instability, impoverishment and childcare burden have somewhat stronger effects on entry rates in block groups than in tracts.

4. Discussion

Investigating the relationship between neighborhood social structure and foster care entry risk at three spatial scales yields two primary findings: 1); Foster care entry rates are significantly higher in neighborhoods with relatively high levels of disadvantage; 2) The strength of the associations changes very little among spatial scales. Also important are the findings that rates of entry in local areas are influenced by social conditions in both local and neighboring area and that the neighborhood social characteristics are geographically clustered. Together, these results suggest that social processes operating in neighborhoods are robust with respect to how place is conceptualized and that they are strongly linked to foster care entry rates, whatever the causal connection between the two. This conclusion bears some discussion.

Residential instability, impoverishment and childcare burden are all positively related to foster care entry rates at all levels of neighborhood aggregation. The magnitude of the associations hardly changes among the scales. The impact of impoverishment is particularly strong relative to the other factors, while residential instability has the weakest association. These findings are consistent with prior studies of neighborhoods and maltreatment risk in other places (Coulton et al., 1999; Coulton et al., 1995; Deccio et al., 1994; Freisthler, 2004; Garbarino & Crouter, 1978). It is not intuitively surprising that the same forces that are linked to maltreatment are also linked to the use of foster care, since out-of-home care is one common response to maltreatment. However, the relationship between neighborhood structure and foster care risk has not previously been established directly and the consistent associations found here suggest that neighborhoods may impact both maltreatment rates and foster care entry rates for the same reasons. For instance, if a lack of community networks and resources threatens some family's abilities to care for children, leading to maltreatment, then those same limitations might make foster care the most viable protective response when informal supports in the neighborhood are weak.

Until the phenomenon is examined over time, it is not possible to identify the mechanisms through which neighborhoods influence the risk of foster care placement. Still, there is mounting evidence that children are at higher risk for placement not only when they live in disadvantaged neighborhoods but also when they live *near* disadvantaged neighborhoods. In the present study, when neighborhoods are modeled as census tracts or block groups, rates of entry in local areas are influenced by social conditions in adjacent locations. Freisthler et al. (2007) found that the number of bars in zip codes was positively related to the foster care entry rate in local and adjacent zip codes over time. They reason that the co-occurrence of bars with poverty and related conditions may signal diminished social controls in those neighborhoods, thereby reducing the likelihood that community members will intervene to prevent or address maltreatment. Similarly, that the effects of impoverishment, residential instability and childcare burden on entry rates appear to spillover into neighboring areas points to the fact that administrative units imperfectly capture neighborhoods as well as to the mobility of residents across neighborhood boundaries.

A final noteworthy finding is that the concentration of most of the neighborhood measures as well as entry rates tends to cluster together. That is, no matter how neighborhoods are delineated, areas with high levels of poverty tend to border other high poverty areas, and areas at high risk for foster care entry tend to be located near other areas with high entry rates. The spatial distribution of foster care entry risk and its correlates, then, is not random. Concentrated impoverishment and its association with other problems like poor health and mortality has been noted elsewhere (Curtis, Southall, Congdon, & Dodgeon, 2004; Lochner, Kawachi, Brennan, & Buka, 2003).

4.1. Implications for child welfare practice and policy

This study has two major implications for child welfare practice and policy. First, if replication bears out these findings, zip codes may be the most practical unit for neighborhood analysis. The large scale of zip codes brings possible practical and analytical benefits. With a few exceptions, the models across scales produce essentially the same results. A spatial lag model is necessary to explain the relationship between neighborhood social organization and entry rates in tracts and block groups but a classical specification with no spatial effects is sufficient for zip codes. The minor differences in the magnitude of the associations between foster care entry rates and impoverishment, residential instability and childcare burden suggest that the choice of scale is not critical for planning services. Zip code maps are simple to generate, view and interpret for child welfare staff and community members. However, without investigation at more than one scale, the effects of adjacent areas would be overlooked, as shown here when neighborhood social attributes are related to entry rates in nearby tracts and block groups but not zip codes. Furthermore, the process by which spatial relationships and spatial scale are considered strengthens the model-building process and offers a set of diagnostic and comparative procedures that can be applied broadly to research on neighborhoods and other small areas.

Second, areas with high levels of residential mobility, impoverishment and childcare burden can be targeted for both preventive and foster care related resource allocation. The findings from the present study point to the complex nature of the within- and between-neighborhood processes that have yet to be identified. Until that time, the findings that foster care entry risk is heightened and concentrated in certain areas and is related to stressful conditions in neighborhoods serves as a starting point for directing child welfare resources to areas most in need.

[3] While block groups are generally smaller subsets of census tracts, in some rural areas they are one in the same because of low population. These two areas are as such.

On the preventive side, impoverished neighborhoods lack resources and may be short of services to support families such as quality childcare and drug treatment programs, which may lead to more children entering foster care rather than being diverted to preventive services. Similarly, high rates of residents moving frequently may mean that families do not live in one neighborhood long enough to develop social capital or knowledge of the resources that are available. On the foster care side, one neighborhood-based strategy is to recruit foster families in areas where the need for safe homes for children entering foster care exceeds the current supply. Another strategy is to build other supports for families in these areas, like kinship support centers and improved physical and economic access to high-quality childcare. The consistently strong relationship between the residential instability, impoverishment and childcare burden factors and foster care entry across scales gives good cause to focus on improving the supply and quality of supports and resources that can help families protect children in neighborhoods with the highest rates of these indicators.

4.2. Limitations and future research

This study suffers from some of the same limitations as much of the prior ecological maltreatment research. Causal links between neighborhood social conditions and foster care entry risk cannot be established without an event history model that follows children over time. Another problem with cross-sectional data is that it cannot distinguish between spatial autocorrelation and spatial heterogeneity. Positive spatial autocorrelation among neighborhood characteristics or rates of entry does not necessarily imply a diffusion process, although diffusion tends to create positive spatial autocorrelation. Cross-sectional data cannot identify the process determining the data. For example, is high foster care entry risk due to contagion or neighborhood effects? Is the decision to remove a child from her home contagious, whereby child welfare workers observe other children being removed from their homes and are therefore subject to peer effects? Or, is it heterogeneity – neighborhood effects – meaning, depleted social capital? The spatial regression models rule out diffusion/contagion effects when no spatial dependence is present among neighborhoods, but in the presence of spatial autocorrelation, the models cannot distinguish between diffusion/contagion and spatial heterogeneity (Anselin, 2003).

Conclusions cannot be drawn regarding the relationship between individual residents and foster care entry risk because the study does not assess the characteristics of maltreating individuals. A related problem persisting in the absence of longitudinal and multilevel data is selection bias. Residents with certain characteristics may self-select to live in certain neighborhoods, either by way of deliberate choice or by default. Spatial event history and spatial hierarchical linear models within a Bayesian framework offer a clear next step for analyses seeking to explain the spatial–temporal dynamics of neighborhood effects as well as distinguishing between social processes operating between and within neighborhoods (Banerjee, Carlin, & Gelfand, 2004).

This study also did not adjust for correlation that arises from the inclusion of siblings. Children from the same family who enter foster care over the same study period are not independent with respect to exogenous factors influencing their outcomes and this correlation biases the standard errors in the statistical models.

While this spatial analysis shows evidence of relationships between some neighborhood social characteristics and foster care entry patterns across neighborhoods, the study cannot determine why these relationships exist. Processes like social capital must be measured directly with qualitative and survey data. The use of this type of data, along with administrative child welfare records that can pinpoint locations associated with various events and can follow cohorts of children over time, could begin to identify the social processes theorized to drive the associations between neighborhoods, maltreatment and foster care entry. Data on the availability of foster homes would determine how supply factors into the equation, net of neighborhood social processes. In the meantime, the identification of neighborhood characteristics related to the use of foster care can be used as a proxy for differential service needs among neighborhoods. For child welfare agencies taking a community approach to service delivery, this information can be used to identify risk by neighborhood in order to more efficiently direct services that may mitigate risk in those areas.

References

Albert, V. N., & Barth, R. P. (1996). Predicting growth in child abuse and neglect reports in urban, suburban, and rural counties. *Social Service Review*, *70*, 58–82.
Annie E. Casey Foundation. (2001). The need for self-evaluation: Using data to guide policy and practice Baltimore.
Annie E. Casey Foundation. (2007). Family to family Retrieved August 1, 2007 from http://www.aecf.org/MajorInitiatives/FamilytoFamily.aspx
Anselin, L. (1988). Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity. *Geographic Analysis*, *20*, 1–17.
Anselin, L. (2002). *Short course: Introduction to spatial data analysis*. Paper presented at the Center for Spatially Integrated Social Science, University of California, Santa Barbara.
Anselin, L. (2003). *GeoDa 0.9 User's Guide*. University of Illinois, Urbana–Champaign and Center for Spatially Integrated Social Science.
Anselin, L. (2005). *Exploring spatial data with GeoDa: A workbook*. Urbana, IL: Center for Spatially Integrated Social Science.
Barth, R., Locklin-Brown, E., Cuccaro-Alamin, S., & Needell, B. (2002). Administrative data on the well-being of children on and off welfare. In M. V. Ploeg, R. A. Moffitt, & C. F. Citro (Eds.), *Studies of welfare populations: Data collection and research issues* Washington, D.C.: National Academy Press.
Bailey, T. C., & Gatrell, A. C. (1995). *Interactive spatial data analysis.* Essex, England: Longman Group Limited.
Banerjee, S., Carlin, B. P., & Gelfand, A. E. (2004). *Hierarchical modeling and analysis for spatial data.* Boca Raton, FL: Chapman & Hall/CRC.
Policy implications in studying neighborhoods. Brooks-Gunn, J., Duncan, G. J., & Aber, J. L. (Eds.). (1997). *Vol. 2 of neighborhood poverty* New York: Russell Sage.
Coleman, J. S. (1988). Social capital in the creation of human capital. *American Journal of Sociology*, *94*, S95–S120.
Coulton, C. J. (2005). The place of community in social work practice research: Conceptual and methodological developments. *Social Work Research*, *29*(2), 73–86.
Coulton, C. J., Korbin, J., Chan, T., & Su, M. (2001). Mapping resident perceptions of neighborhood boundaries: A methodological note. *American Journal of Community Psychology*, *29*, 371–383.
Coulton, C. J., Korbin, J. E., & Su, M. (1999). Neighborhoods and child maltreatment: A multi-level study. *Child Abuse and Neglect*, *23*(11), 1019–1040.
Coulton, C. J., Korbin, J. E., Su, M., & Chow, J. (1995). Community level factors and child maltreatment rates. *Child Development*, *66*, 1262–1276.
Curtis, S., Southall, H., Congdon, P., & Dodgeon, B. (2004). Area effects on health variation over the life-course: Analysis of the longitudinal study sample in England using new data on area of residence in childhood. *Social Science and Medicine*, *58*, 57–74.
Deccio, G., Horner, W. C., & Wilson, D. (1994). High-risk neighborhoods and high-risk families: Replication research related to the human ecology of child maltreatment. *Journal of Social Service Research*, *18*(3/4), 123–137.
Drake, B., & Pandey, S. (1996). Understanding the relationship between neighborhood poverty and specific types of child maltreatment. *Child Abuse and Neglect*, *20*(11), 1003–1018.
Ernst, J. S. (2001). Community-level factors and child maltreatment in a suburban county. *Social Work Research*, *25*(3), 133–142.
Freisthler, B. (2004). A spatial analysis of social disorganization, alcohol access, and rates of child maltreatment in neighborhoods. *Children and Youth Services Review*, *26*(9), 803–819.
Freisthler, B., Gruenwald, P. J., Remer, L. G., Lery, B., & Needell, B. (2007). Exploring the spatial dynamics of alcohol outlet and child protective services referrals, substantiations, and foster care entries. *Child Maltreatment*, *12*(2), 114–124.
Freisthler, B., Merritt, D. H., & LaScala, E. A. (2006). Understanding the ecology of child maltreatment: A review of the literature and directions for future research. *Child Maltreatment*, *11*(3), 263–280.
Fryer, G. E. J., & Miyoshi, T. J. (1995). A cluster analysis of detected and substantiated child maltreatment incidents in rural Colorado. *Child Abuse and Neglect*, *19*(3), 363–369.
Garbarino, J., & Crouter, A. C. (1978). Defining the community context for parent–child relations: The correlates of child maltreatment. *Child Development*, *49*, 604–616.
Garbarino, J., & Kostelny, K. (1992). Child maltreatment as a community problem. *Child Abuse and Neglect*, *16*, 455–464.
Garbarino, J., & Sherman, D. (1980). High-risk neighborhoods and high-risk families: The human ecology of child maltreatment. *Child Development*, *51*, 188–198.
Greene, W. H. (2003). *Econometric analysis.* Upper Saddle River, NJ: Prentice Hall.
Korbin, J. E., Coulton, C. J., Chard, S., Platt-Houston, C., & Su, M. (1998). Impoverishment and child maltreatment in African American and European American neighborhoods. *Development and Psychopathology*, *10*, 215–233.
Lochner, K. A., Kawachi, I., Brennan, R. T., & Buka, S. L. (2003). Social capital and neighborhood mortality rates in Chicago. *Social Science and Medicine*, *56*, 1797–1805.

Moran, P. (1950). Notes on continuous stochastic phenomena. *Biometrika*, *37*, 17−23.
Needell, B., Webster, D., Armijo, M., Lee, S., Dawson, W., Magruder, J., et al. (2008). Child welfare services reports for California Retrieved March 15, 2008, from University of California at Berkeley Center for Social Services Research website. URL: <http://cssr.berkeley.edu/ucb_childwelfare>
Needell, B., Webster, D., Cuccaro-Alamin, S., Armijo, M., Lee, S., Brookhart, A., et al. (2005). Child welfare services reports for California Retrieved May 3, 2005, from University of California at Berkeley Center for Social Services Research website. URL: <http://cssr.berkeley.edu/CWSCMSreports/>
Sampson, R. J. (1999). What community supplies. In R. Ferguson, & W. T. Dickens (Eds.), *Urban problems and community development* Washington, D.C.: Brookings Institute.
Shaw, C., & McKay, H. (1942). *Juvenile delinquency in urban areas.* Chicago: University of Chicago Press.
Spearly, J. L., & Lauderdale, M. (1983). Community characteristics and ethnicity in the prediction of child maltreatment rates. *Child Abuse and Neglect*, *7*, 91−105.
Tratner, W. I. (1994). *From poor law to welfare state: A history of social welfare in America.* New York: The Free Press.
Wong, D. (1996). Aggregation effects in geo-referenced data. In S. L. Arlinghaus (Ed.), *Practical handbook of spatial statistics* New York: CRC Press.
Young, G., & Gately, T. (1988). Neighborhood impoverishment and child maltreatment: An analysis from the ecological perspective. *Journal of Family Issues*, *9*, 240−254.
Zuravin, S. J. (1986). Residential density and urban child maltreatment: An aggregate analysis. *Journal of Family Violence*, *1*, 307−322.