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Neighborhood collective efficacy and dimensions of diversity: a multilevel analysis

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Abstract. Collective efficacy is becoming an increasingly important concept within the social and health sciences as researchers question how the social environment of a neighborhood influences a host of individual psychological, behavioral, and health outcomes. We investigate whether ethnic as well as other dimensions of neighborhood-level diversity are associated with collective efficacy. Survey data are used to capture perceptions of neighborhood cooperation and social cohesion for 26 344 survey respondents in southeast Pennsylvania; US Census data are used to capture neighborhood concentrated disadvantage and residential mobility, as well as diversity along a range of dimensions, including ethnicity, birthplace, household type, occupation, income, and educational attainment. Multilevel modeling is employed to test the association of various dimensions of neighborhood diversity with individual-level perceptions of neighborhood cooperation and social cohesion, while controlling for individual and other neighborhood-level variables. Results suggest that low collective efficacy is associated with diversity in cultural characteristics such as ethnicity, birthplace, and household type. We ascribe these findings to patterns of neighborhood transition, or churning, where high rates of neighborhood in-migration and out-migration act to weaken collective efficacy. Diversity, both in educational attainment and in income, however, are associated with high neighborhood collective efficacy, and are not related to neighborhood churning.

Keywords: neighborhood social capital, collective efficacy, diversity, social cohesion, neighborhood effects, HLM

1 Introduction

Neighborhood collective efficacy captures the willingness of neighbors to work together on community issues as well as the degree of social interaction among neighbors and the sense of belonging a resident feels towards his or her community (Sampson et al, 1997). Outcomes as diverse as crime and delinquency, mental health, substance use, and child development have been linked to indicators of collective efficacy at the neighborhood level (Sampson et al, 1999; Stahler et al, 2009). Questions remain, however, as to what forces weaken or strengthen a community's collective efficacy.

Recently, scholars have begun to address the role of ethnic diversity in influencing a neighborhood's capacity for collective efficacy. The key principle that links diversity to collective efficacy is homophily—the tendency of individuals to form social connections with people similar to themselves (McPherson et al, 2001). Some scholars have argued that a neighborhood with an influx of ethnically diverse residents should be expected to have weaker collective efficacy than an ethnically homogeneous one (Goodhart, 2004), while others have noted that ethnic diversity may increase social cohesion over longer time periods, as contact among individuals of different ethnicities leads to acceptance and trust of people from backgrounds different from one's own (Letki, 2008; Putnam, 2007).

The purpose of this research is to investigate whether ethnic as well as other dimensions of diversity are associated with neighborhood collective efficacy after controlling for established mechanisms of concentrated disadvantage and residential mobility. The handful of studies that have explicitly addressed the role of diversity in collective efficacy have focused primarily on ethnic diversity to the exclusion of other dimensions of diversity. However, the principle of homophily would suggest that diversity along dimensions other than ethnicity would also play a role in the formulation of neighborhood collective efficacy. We focus, therefore, not only on ethnic diversity, but also on a variety of other characteristics that may play a role in formulating collective efficacy, including birthplace, education, and income.

Our analysis focuses on the five counties of southeast Pennsylvania, located in the Mid-Atlantic region of the US and including the city of Philadelphia. This study area has characteristics similar to many other US metropolitan regions: it encompasses a large urban center as well as its suburbs and exurbs, with a total population of approximately four million. The population is ethnically diverse: 66% White, 21% African American, and 13% other (including Hispanics and Asians). The region as a whole is also economically diverse, and includes several urban and suburban areas exhibiting substantial poverty concentration in proximity to neighborhoods of notable wealth. To test for the influence of diversity on collective efficacy we use a multilevel model design (Snijders and Bosker, 1999) in which individuals may be considered to spatially nest within neighborhoods. We hypothesize that individual perceptions of neighborhood collective efficacy will be associated not only with the personal characteristics of the individual but also with the character of the neighborhoods within which they reside.

2 Neighborhood collective efficacy

2.1 Definitions

The concept of neighborhood collective efficacy can be understood as a specific form of group-level social capital. Social capital derives from social relations between and among individuals that lead to productive value for the actors involved (Coleman, 1988). It can produce various forms of value such as monetary gain, increased access to information, and the facilitation of norms of behavior that encourage people to act in a collective manner even though it may be contrary to their self-interest. Social capital relies on relationships based on norms, trust, and reciprocity that people build over time and capitalize upon when necessary (Putnam 2000).

In a similar way, neighborhood social capital can be understood generally as productive activity embedded in the dynamics of group-level relations. However, group relationships need to be understood not only by connections among individuals, but also by the interconnectivity between people and groups. Neighborhood social capital is a form of group-level interconnectedness that applies to place communities such that it is formed and nurtured by the intersection of people and place, and thus an understanding of neighborhood social capital must include the organizational and structural elements of place (Temkin and Rohe, 1998). As a resource stock for communities, neighborhood social capital can foster important forms of informal social control on which communities often rely to maintain well-functioning neighborhoods (Twigg et al, 2010).

Neighborhood collective efficacy is similar in principle to neighborhood social capital in that it is a group-level social resource, but differs in that collective efficacy is episodic in nature (Lochner et al, 1999). It can be considered to be the community social connections which lead to participation and mobilization toward a specific common goal or action

(Sampson et al, 1999) and, in that sense, is related to mechanisms of informal social control. Strong neighborhood collective efficacy is illustrated by, say, neighbors coming together to develop a community recreation center or to block an unwanted land-use development. In this paper, we use the term ‘neighborhood collective efficacy’ generally to capture aspects both of mobilization toward a specific community-level goal, which we refer to as ‘neighborhood cooperation,’ as well as the resource stock of social capital that exists within a neighborhood, which we refer to as ‘social cohesion’.

2.2 Social mechanisms of neighborhood collective efficacy

Group-level processes are not simply the byproduct of a collection of individual actions, but are influenced by the social–structural elements within which those individual actions are situated (Van Vliet and Burgers, 1987). Thus, when investigating influences on neighborhood collective efficacy, researchers often consider a range of compositional as well as contextual mechanisms. Regarding compositional influences, there is general agreement that the characteristics of the people in an area—for example, their age, income, race, ethnicity, educational attainment, and religion influence that place’s collective efficacy (McPherson et al, 2001).

An additional consideration is that the longer one resides in a single location, the greater the opportunity for making connections (Putnam, 2000). Thus residential stability is considered an asset for communities and a determinant of neighborhood collective efficacy (Guest et al, 2006; Sampson et al, 1999). Researchers also focus on indicators of concentrated disadvantage as a possible factor in dampening collective efficacy (Letki, 2008; Sturgis et al, 2010; Twigg et al, 2010). High levels of neighborhood poverty and unemployment, as well as compromised infrastructure, as indicated by high building-vacancy rates, are posited to negatively affect the amount and quality of social interaction among neighbors (Letki, 2008).

Another factor theorized to influence neighborhood collective efficacy is the level of attachment that individuals feel toward a place (Low and Altman, 1992; Temkin and Rohe, 1998; Tuan, 1980). Place attachment is the process of identifying closely with a certain locale through ‘people–place bonding’, whereby a physical place becomes central to one’s emotional fabric (Low and Altman, 1992, page 4). Place attachment grows from memories of past experiences, shared histories, and an appreciation of place that become an extension of self-identity (Corcoran, 2002; Tuan, 1980). Place attachment often fosters trust relationships that encourage civic action (Payton et al, 2005). Notably, residential stability is tied to increased place attachment (Kasarda and Janowitz, 1974).

A related concept is that of sense of community, which can be considered the product of bonds among people and the social structure of place (Lochner et al, 1999). As a place’s sense of community gradually builds, that community’s history and texture play a role in its capacity for neighborhood collective efficacy. Communities cultivate a certain culture over time and differ in their longstanding tendencies toward a civic orientation (Molotch et al, 2000; Putnam, 1993). These traditions mark neighborhoods, cities, and regions in distinctive ways and shape the experiences and perceptions that people associate with place (Dayanim, 2011).

2.3 Diversity and neighborhood collective efficacy

The strong relationship between homogeneity and social networks, often called ‘homophily’, is well known (McPherson et al, 2001). The thrust of the argument is that connections occur more frequently between people who possess similar characteristics. Race and ethnicity are high among distinguishing characteristics for self-sorting, but religion, education and social class, behavior, and life cycle also account for strong tendencies to seek out others like oneself.

Since frequent and casual social interaction is cited as an important influence on the potential for neighborhood collective efficacy (Bellair, 1997; Putnam and Feldstein, 2003), it follows that diversity—which, according to the theory of homophily, may lessen such interaction—could potentially dampen the prospects for strong levels of neighborhood cooperation and social cohesion. Research on diversity and collective efficacy clearly points to this negative relationship (Coffé and Geys, 2006; Goodhart, 2004; Guest et al, 2008; Putnam, 2007; Sturgis et al, 2010).

However, recent scholarship has brought a more nuanced perspective to an understanding of the relationship between diversity and neighborhood collective efficacy. Twigg et al (2010), as well as Letki (2008), acknowledge the important role which diversity plays in enervating collective efficacy, but they also point to concentrated disadvantage as a key factor. Coffé (2009) finds that municipalities with lower incomes actually exhibit higher levels of social capital, whereas Guest et al (2008) find that residential stability and diversity are equally important in predicting levels of trust. Sturgis et al (2010) distinguish between two kinds of trust—general trust and trust in people one knows personally—and find that the negative effects of diversity are associated more with the latter. Putnam (2007), on the other hand, posits that ethnic diversity in the short run elicits in people the tendency to constrict their social networking tendencies across the board, even with those who are similar to them. Morello-Frosh et al (2002, page 152) argue that places in the process of ethnic diversification and transition—what they term neighborhood 'ethnic-churning'—have a diminished capacity for collective efficacy, possibly due to a weakened web of social networks. Notably, the bulk of research measuring the effects of diversity on collective efficacy has focused on the race or ethnicity dimension. The few studies that have considered other sociodemographic characteristics point both to age and to affluence as influences (Guest et al, 2006; 2008; Sampson et al, 1999).

In the present research we seek to investigate the association among several aspects of diversity with neighborhood collective efficacy. Due to principles of homophily, we consider that these aspects of diversity will have a negative association both with the neighborhood cooperation and with the social cohesion dimensions of collective efficacy. The focus here is not only on ethnic diversity but also on variation in age, type of employment, income, household type, birthplace, and educational attainment—all of which are factors that we hypothesize may encourage, or discourage, individuals to form social bonds with others in their community. We test the relationship between different aspects of diversity and collective efficacy while accounting for neighborhood characteristics for which previous researchers have found relationships: concentrated disadvantage, population density, and residential mobility.

3 Data and methods

3.1 Individual-level data and outcomes

Data on individuals were collected from the Philadelphia Health Management Corporation's Household Health Survey (HHS). The HHS collects health status, health care, and related information about adults and children residing in southeast Pennsylvania, including Philadelphia, Montgomery, Bucks, Chester, and Delaware counties (figure 1). It has been administered since 1983 and more recently has been undertaken every two years. The survey is administered to over 10 000 randomly selected adults, each in an individual household, by telephone (including cell phone), using a stratified random sampling and random digit-dialing strategy that is intended to capture adequate representation across geographic areas and over population subgroups. If the selected adult was not available due to health or language restrictions, the interview proceeded with another, related, adult living in the same household. The 2000 US Bureau of the Census tract identification number is attached to each case in the sample to provide a georeference for each household.

Figure 1. The five-county southeast Pennsylvania region.

The present analysis uses unweighted data from the 2006, 2008, and 2010 surveys. Data from the three survey years were aggregated to form a single cross-sectional data set. Variables capturing basic demographic and socioeconomic indicators were extracted from the HHS data for this study, including the respondent's sex, age, ethnicity (eg, non-Hispanic White, non-Hispanic African American, Hispanic, and so on), poverty, and educational attainment. Table 1 describes these variables and provides descriptive statistics. The dataset contains 26 344 cases.

Table 1. Descriptive statistics of the survey sample ($N = 26\,344$).

Variable	Definition	Number	Percentage
Female	Respondent is female	17 451	66.3
Ethnicity	Ethnicity of the respondent		
White	Respondent is White, not Hispanic	17 641	67.0
Black	Respondent is Black, not Hispanic	5 594	21.2
Latino	Respondent is Hispanic	1 767	6.7
Other ethnicity	Respondent is another ethnicity	1 332	5.1
Poor	The household income is below the federal poverty threshold	2 171	8.2
College	The respondent has acquired a high school diploma and completed at least some college	15 829	60.1
Age	Age of the respondent (in years)	mean = 50.2, SD = 16.5	

The outcome variables relating to neighborhood collective efficacy were also collected from the HHS data. We note that different studies have operationalized collective efficacy in a variety of ways: some have used indirect indicators, such as the presence of civic or other community organizations, while others have used indices derived from several survey questions regarding perceptions of trust and community participation. We are fortunate to have the HHS survey data which contain questions that are specifically intended to elicit perceptions of collective efficacy, although the number of survey questions available in the HHS data is less than has been used in some other studies. The first collective efficacy variable derived for the present study, 'neighborhood cooperation', was calculated from

Table 2. Collective efficacy outcome variables.

Variable	Survey question	Response	Recode	N	Percentage
Neighborhood cooperation	Using the following scale, please rate how likely people in your neighborhood are willing to help their neighbors with routine activities such as picking up their trash cans, or helping to shovel snow.	1 = never 2 = rarely	1	7544	28.6
		3 = sometimes	2	7993	30.4
		4 = often	3	6785	25.8
		5 = always	4	4012	15.2
Social cohesion	Please tell me if you strongly agree, agree, disagree, or strongly disagree with the following statement: I feel that I belong and am a part of my neighborhood.	1 = strongly disagree 2 = disagree 3 = agree 4 = strongly agree			
	Please tell me if you strongly agree, agree, disagree, or strongly disagree with the following statement: Most people in my neighborhood can be trusted.	1 = strongly disagree 2 = disagree 3 = agree 4 = strongly agree			
			1	5488	20.8
			2	4307	16.4
			3	11060	42.0
			4	5479	20.8

the first survey question reported in table 2. We recoded the raw tabulations from the five-category Likert scale into four categories to attain a more equal distribution of the outcome variable, where the two lowest categories were combined into a single category, as relatively few respondents indicated that neighbors ‘never’ helped each other. This recoding resulted in a four-category ordinal variable where a value of ‘1’ indicates a low degree of neighborhood cooperation and a value of ‘4’ indicates a high degree of neighborhood cooperation.

The second collective efficacy outcome variable, ‘social cohesion’, was derived from two survey questions shown in the lower part of table 2, each of which is coded on a four-category Likert scale. We took the mean of the two questions, and then recoded the results into a four-category ordinal scale where a value of ‘1’ indicates a low degree of social cohesion and a value of ‘4’ indicates a high degree of social cohesion. Because the raw data were highly skewed, with few respondents expressing feelings at the lowest possible scores of social cohesion, the recoding aggregated raw mean values of 1–2.5 into the lowest ordinal category ‘1’, a raw mean value of 3 was coded as the ordinal category ‘2’, a raw mean value of 3.5 was coded as the ordinal category ‘3’, and a raw mean value of 4 was coded as the ordinal category ‘4.’ This classification provided a more equal distribution of this outcome variable, as shown in table 2.

3.2 Creating neighborhood boundaries

We used the 2005–09 five-year sample of the American Community Survey (ACS) to capture neighborhood mechanisms which we hypothesize influence neighborhood cooperation and social cohesion. The ACS, administered by the US Bureau of the Census, is the primary US national survey on social, economic, housing, and demographic topics and is delivered to approximately three million addresses in the US annually. As is customary with ACS data, we use five years of ACS data to provide a dense enough sample for reliable estimation of socioeconomic character at the census-tract level, where the average area of a tract in our study region is 5.8 km^2. ACS data are used here to indicate concentrated disadvantage, residential mobility, and various measures of ethnic and other aspects of diversity.

Concentrated disadvantage is operationalized as an index variable calculated by summing the z-scores of the following three census variables: the percentage of households receiving public assistance income, the percentage of housing units that are vacant, and the percentage of the civilian population aged 16 years and older who are unemployed (Cronbach's $\alpha = 0.84$).

Residential mobility was operationalized by summing the z-scores of three additional census variables that are intended to capture housing tenure and turnover in residency: the percentage of occupied housing units occupied by renters, the percentage of occupied housing units in which the occupant had moved into the unit since 2000, and the percentage of the population aged one year and up who had moved into their current residence within the past year from outside the county (Cronbach's $\alpha = 0.73$). In addition, population density was calculated as the total population over the area of the tract in square miles, in order to control for the degree of 'urbanness'.

We note that one of the major challenges in employing multilevel modeling designs for spatial data, where level-1 point observations intended to capture the locations of individuals are nested within level-2 neighborhoods operationalized as polygons, is ensuring that the boundaries of the level-2 spatial units actually reflect the spatial process under investigation (Fotheringham et al, 2000). More practically, one must also be concerned about the number of level-1 observations contained within each level-2 spatial unit.

We addressed this issue by aggregating adjacent tracts with similar socioeconomic profiles to form more coherent neighborhoods. For this purpose we employed a regionalization technique called REDCAP (regionalization with dynamically constrained agglomeration and partitioning), developed by Guo (2008), that clusters a set of spatial units into a set of spatially contiguous neighborhoods. This regionalization technique identifies optimal neighborhoods by maximizing within-neighborhood homogeneity over a set of input spatial units with associated attribute values. The technique also provides an option to preserve a minimum within-neighborhood population. For details on the regionalization algorithm the reader is referred to Guo (2008).

In the present study, we applied REDCAP to the census-tract data, after removing the handful of tracts with zero or near-zero population, such as those containing parks and industrial areas. The algorithm was applied using the population density, concentrated disadvantage, and residential mobility variables to identify the most similar, adjacent tracts to merge into single neighborhoods. In order to generate neighborhoods with sufficient numbers of level-1 cases within each level-2 spatial unit, we enforced a requirement that all derived neighborhoods contain a minimum of ten survey respondents. The regionalization yielded a set of 520 neighborhoods.

3.3 Neighborhood-level variables

The population density, concentrated disadvantage, and residential mobility variables were then recalculated at the neighborhood level. We consider these indices neighborhood-level controls, as they are well known to contribute to neighborhood collective efficacy (Sampson et al, 1999; Sturgis et al, 2010; Twigg et al, 2010). We then derived a set of variables of interest that are intended to capture different aspects of neighborhood-level diversity, including diversity in ethnicity, age, education, income, occupation, household type, and birthplace (table 3). For each of these features, the diversity in each neighborhood was calculated based on a local entropy score, E, given as

$$E_j = \sum_{i=1}^{n}\left[\left(\frac{p_{ij}}{p_j}\right)\ln\left(1\Big/\frac{p_{ij}}{p_j}\right)\right]\Big/\ln n \,, \tag{1}$$

where P_{ij} is the population of population group i in neighborhood j, P_j is the population in neighborhood j, and n is the number of population groups. The value of E_j varies from 0

Table 3. Definition and calculation of neighborhood-level diversity variables.

Diversity variables	Universe of population	Categories of population groups
Ethnicity entropy	total population	White; Black; Hispanic; Asian; Other
Age entropy	total population	0–4; 5–17; 18–34; 35–54; 55 and over
Education entropy	population 25 years and over	no high school diploma; high school diploma; bachelors degree; graduate or professional degree
Income entropy	total households	\$0–\$29 999; \$30 000–\$59 999; \$60 000–\$99 999; \$100,000 and over
Occupation entropy	population aged 16 years and over, civilian, employed	management, service, sales, farming, construction, production/transportation
Household (HH) type entropy	total households	family—married couple; family—single parent; nonfamily—living alone; nonfamily—not living alone
Birthplace entropy	total population	born in Pennsylvania; born in another US state; born in a foreign country

to 1, with higher values indicating greater diversity and a unit with equal proportions of all population groups having an E_j value of 1 (Apparicio et al, 2008). This formula was applied to calculate variables that capture ethnicity entropy, age entropy, and so on for each aspect of diversity, where the population groups for each aspect of diversity are given in table 3.

3.4 Analytical strategy

In order to develop a multivariate model that incorporates the influence of the neighborhood-level variables (level 2) on an individual-level outcome, while also accounting for individual-level explanatory variables (level 1), we utilize a multilevel regression model design. Multilevel modeling has been applied to a variety of spatial datasets where individuals may be seen to nest within neighborhoods in a hierarchical framework (Grunwald et al, 2010; Subramanian, 2010). In the present study level 1 is composed of the survey response data ($N = 26\,334$) and level 2 is composed of the neighborhood characteristics ($N = 520$). The mean number of individuals within each neighborhood is thus 51 (standard deviation = 16).

Because the outcomes of interest—neighborhood cooperation and social cohesion—are both ordinal in nature, a multilevel ordinal modeling framework employing random intercepts was applied (Hedeker, 2008). Such an approach allows the mean of the outcome to vary among neighborhoods and supports the estimation of the amount of variance in the outcome for which each level is responsible. This modeling approach has been used in a variety of applications for ordinal outcome variables in which the data are structured hierarchically, including analyses of perceptions of health and crime where individuals are seen to be nested within households and communities (Chen et al, 2008; Gracia and Herrero, 2008). Mathematically, if i denotes the level-1 observations and j denotes the level-2 units, then the level-1 equation for a multilevel ordinal model with a single level 1 covariate x_{ij} and a single level-2 covariate x_j may be expressed as the logit

$$\ln\left(\frac{p_{ij}}{1 - p_{ij}}\right) = \beta_{0j} + \beta_{1j} x_{ij} \ , \tag{2}$$

where p is the probability of an ordinal response value and β is a regression coefficient to be estimated (Hedeker, 2008). The level-2 model may then be expressed as

$$\beta_{0j} = \beta_0 + \beta_2 x_j + \delta_{0j} \ , \tag{3}$$

$$\beta_{1j} = \beta_1 + \beta_3 x_j + \delta_{1j} \ , \tag{4}$$

where δ_j is the random effect at level 2.

Note that in ordinal regression the cumulative probability of an ordinal response is conceptualized as a function of a series of thresholds applied to an unobserved continuous latent variable. Thus, given an ordinal outcome $k = \{1, 2, 3, 4\}$, as in the present study, the multilevel ordinal model solves for the effect at level 2 that results in the likelihood of an observation having an ordinal outcome value $k = 1$, $k \leqslant 2$ and $k \leqslant 3$ (and the probability of $k \leqslant 4 = 1$). Therefore, under the assumption of proportional odds (as in the present study), the odds ratio expressed in the round brackets in equation (2) captures the effect of the explanatory variable on moving the ordinal response from one ordinal category to the next higher adjacent ordinal category.

Calculating the intraclass correlation coefficient (ICC) in multilevel ordinal models differs from its calculation in conventional multilevel models with a continuous outcome variable, where conventionally $\mathrm{ICC} = V_\mathrm{N}/(V_\mathrm{N} + V_\mathrm{I})$ and where V_N is the neighborhood-level variance and V_I is the individual-level variance. In the present study we employ the linear threshold model for calculating ICC for ordinal outcome data (Snijders and Bosker 1999), where V_I follows a logistic distribution with a mean of zero and a variance of $\pi^2/3 \cong 3.29$, and therefore $\mathrm{ICC} = V_\mathrm{N}/(V_\mathrm{N} + 3.29)$, an approach used in several other studies employing multilevel ordinal or logistic models (Chen et al, 2008; Theall et al, 2011). Using this approach, we calculate the ICC for neighborhood cooperation as 0.163/(0.163 + 3.29) = 4.7%, and the ICC for social cohesion as 0.416/(0.416 + 3.29) = 11.2%.

The analysis proceeds for each outcome separately. After calculating the empty, or null, model, which we use to derive the ICC, we model the level-1 covariates in isolation (model 1). We then test in a neighborhood-level-only model whether the diversity variables are significant when combined with the control variables (model 2). We then calibrate a final model that combines the individual-level variables with those neighborhood-level variables that were found to be significant in the neighborhood-level-only model (model 3). All continuous variables, with the exception of age, were transformed by taking the z-score in order to grand-mean center the variables and facilitate interpretation of the results. In addition, the age variable was encoded in decades, as opposed to single years, to aid in the interpretation of the results. Models were estimated using restricted penalized quasi-likelihood (PQL) in HLM 6.06 (Raudenbush et al, 2004). A review of the Pearson correlations among explanatory variables, as well as the variance inflation factor (VIF) diagnostics, indicated that multicollinearity was not problematic for any of the models presented here.

4 Results

Table 4 shows the results of the multilevel ordinal model of neighborhood cooperation in models 1, 2, and 3, where the odds ratio for each variable included in the model is reported. Model 1 includes only the individual-level variables, all of which are significant. For the categorical explanatory variables the odds ratio may be interpreted to read that the presence of that categorical characteristic in the individual increases or decreases the likelihood of a one-step increase in the ordinal response, compared with the reference category. For example, females are 1.13 times more likely to rank their neighborhood cooperation one category higher than males. Since the outcome variable is composed of four ordinal categories, females are 1.44 times more likely than males to rank their neighborhood cooperation the highest ordinal category compared with the lowest ($1.13 \times 1.13 \times 1.13 = 1.44$).

For continuous variables the odds ratio is interpreted for a one-unit change in the explanatory variable. For example, for the variable age, which is encoded in decades, each additional decade in the age of the respondent increases the likelihood of selecting a higher neighborhood cooperation category by a factor of 1.14. Perceptions of neighborhood cooperation are also enhanced, on average, by higher individual educational attainment

Table 4. Results of multilevel ordinal regression of neighborhood cooperation and social cohesion ($N = 26\,344$).

	Neighborhood cooperation			Social cohesion		
Variable	model 1	model 2	model 3	model 4	model 5	model 6
Individual variables						
Female	1.13***		1.13***	0.99		1.00
Age	1.14***		1.13***	1.24***		1.23***
Ethnicity (ref = White)						
Black	0.67***		0.80***	0.54***		0.68***
Latino	0.68***		0.83***	0.61***		0.77***
Other ethnicity	0.84***		0.90*	0.76***		0.82***
Poor	0.66***		0.70***	0.64***		0.68***
College	1.15***		1.10***	1.34***		1.26***
Neighborhood variables						
Controls						
Population density		0.95**	0.97		0.88***	0.91***
Concentrated disadvantage		0.81***	0.87*		0.74***	0.83***
Residential mobility		0.95*	0.95*		0.95***	0.95***
Diversity						
Ethnicity entropy		0.89***	0.91***		0.88***	0.90***
Age entropy		1.02			1.01	
Education entropy		1.07***	1.06***		1.11***	1.11***
Income entropy		1.02			1.10***	1.06***
Occupation entropy		0.98			0.92***	0.95**
Household type entropy		1.00			0.94***	0.96*
Birthplace entropy		0.96*	0.96*		1.00	
Variance component	0.066	0.021	0.017	0.147	0.021	0.06

*$p<0.05$, **$p<0.01$, ***$p<0.005$.
Note. Values are odds ratios (except variance component).

(ie, attending at least some college) and are suppressed by poverty and minority status (Black, Hispanic, or other non-White status) compared to being White.

In model 2 we explore the relationship between the neighborhood-level-only traits and overall mean neighborhood-cooperation. Because the neighborhood-level variables are standardized, their odds ratios may be interpreted as the effect on the likelihood of being in a higher neighborhood cooperation category given a one standard deviation change in the explanatory variable. For example, with each standard deviation increase in population density, a respondent is 0.94 times as likely to report a higher neighborhood-cooperation response; that is, respondents in more densely populated neighborhoods tend to perceive lower neighborhood cooperation. As expected, increasing concentrated disadvantage and residential mobility are also associated with more negative perceptions of neighborhood cooperation.

Several diversity variables are also significant: increasing diversity in ethnicity and birthplace are associated with perceptions of lower neighborhood cooperation, and diversity in education is associated with higher neighborhood cooperation. The neighborhood-level explanatory variables together explain 87% of the between-neighborhood variance $(0.163 - 0.021)/0.163 = 87\%$. When the level-1 variables and the significant level-2 variables from the previous models are combined into a single model—model 3—only population density is no longer significant.

Results of the multilevel ordinal regression of social cohesion are reported in table 4, (models 4, 5, and 6). In the individual-level only model (model 4), all variables are significant, with the exception of the female variable. The other results are similar to those of the analogous model of neighborhood cooperation, where poverty and minority status act to suppress the perception of social cohesion while higher educational attainment and being older tend to enhance it.

At the neighborhood level, model 5 (table 4) indicates that social cohesion is suppressed by a respondent residing in neighborhoods with high population density, concentrated disadvantage, and residential mobility. Notably, even in the presence of these control neighborhood-level variables, many other diversity neighborhood level variables have a significant relationship with social cohesion. Social cohesion is suppressed by diversity in ethnicity, occupation, and household type, and is enhanced by diversity in education and income. Nearly 95% of the between-neighborhood variance is explained by the level-2 explanatory variables. When the individual-level and significant neighborhood-level variables are combined in a single model—model 6—all variables remain significant. On average, dimensions of neighborhood diversity have a stronger relationship with individual perceptions of social cohesion compared with neighborhood cooperation.

5 Discussion

Though it is important to keep in mind that different authors have operationalized collective efficacy in different ways, we note that our results for the individual and control variables are generally consistent with previous research described by authors such as Sampson et al (1997), Guest et al (2006), Putnam (2007), and Twigg et al (2010). Like these authors, we found that older respondents tend to perceive greater neighborhood collective efficacy, in terms both of neighborhood cooperation and of social cohesion, compared with younger respondents. With age typically comes greater residential and economic stability and investment in the future, that catalyzes community involvement. It is notable, however, that age entropy is not significantly associated with either measure of collective efficacy in our multilevel models. We also found that women tend to have greater perceptions of neighborhood cooperation than do men, though we did not find this gender effect for social cohesion.

Higher socioeconomic status at the individual level, as reflected by college education and income above the poverty level, was found to increase perceptions of neighborhood collective efficacy, which may reflect preconditions for participation in community activities, in terms of the availability of free time to participate and past experience with organized social and/or community projects (Kasarda and Janowitz, 1974; Twigg et al, 2010). Minority (non-White) status of the respondent was also found to be associated with lower perceptions both of neighborhood cooperation and of social cohesion, controlling for neighborhood traits, which may indicate minority respondents' concerns for competition over resources, struggles with cultural dominance, or fear of discrimination (Coffé, 2009; Leigh, 2006).

At the neighborhood level we found that concentrated disadvantage and residential mobility are both negatively associated with neighborhood collective efficacy. As in many urban areas, disadvantaged neighborhoods in Philadelphia and its suburbs not only suffer from economic deprivation but also attendant social problems of chronic unemployment, crime, and substance use. Housing abandonment and dilapidation of physical infrastructure are also typical and provide visual markers of a lack of social control over the environment (Kelling and Wilson, 1982). Such forces can combine to weaken social ties, and mitigate cooperative projects, among neighbors. Interestingly, however, we also found cross-level interaction effects between individual-level and neighborhood-level indicators of disadvantage, where the occurrence of poverty at the individual level suppresses both neighborhood cooperation (interaction term coefficient = 0.13, $p < 0.005$) and social cohesion (interaction term coefficient = 0.15, $p < 0.005$) to a greater degree in more advantaged neighborhoods. We speculate that this interaction effect likely occurs because of the cultural and/or social isolation that a poor person may feel when living in a neighborhood where most others are wealthier than themselves.

Intuitively, residential mobility suppresses neighborhood collective efficacy by mitigating the length of time neighbors have to form relationships with one another, thus possibly undermining the development of a sense of community. In addition, residents who see themselves as staying for a short time may be less inclined to develop social relationships with neighbors and to participate in community projects.

As with Putnam (2007) and others, our results support the argument that, in general, ethnic diversity is associated with lower neighborhood collective efficacy. These findings support the natural extension of the principles of homophily in the context of ethnicity to neighborhood collective efficacy. We note that some authors have argued that despite findings that support the negative association of ethnic diversity with neighborhood collective efficacy, the role of ethnic diversity is subservient to that of concentrated disadvantage (Letki, 2008; Twigg et al 2010). Our work supports this contention to some extent, as the effect of size of concentrated disadvantage was found to be of greater magnitude than that of ethnic diversity. That said, our results indicate that in more ethnically diverse neighborhoods the tendency for neighbors to work together and form social bonds is less than in ethnically homogeneous neighborhoods, even after accounting for gender, ethnicity, and socioeconomic status at the individual level, as well as concentrated disadvantage and residential mobility.

We also found that diversity measures other than ethnicity were negatively related to neighborhood collective efficacy. Diversity in birthplace (ie, born in Pennsylvania, in another state, or outside the US) is associated with lower perception of neighborhood cooperation. This surprising finding may be linked to the notion that a community's longstanding history and texture plays a role in its capacity for collective efficacy. In this way, places develop a unique culture over time; when a neighborhood is composed mostly of those born and raised within that distinct shared way of life, cooperation is more likely to ensue. Furthermore, diversity in occupation as well as in household type (eg, family versus nonfamily households) is associated with lower perception of social cohesion.

On the other hand, we find that diversity in educational attainment is associated with higher, not lower, neighborhood cooperation and social cohesion, which contradicts previous research (Costa and Kahn, 2003; Leigh, 2006). The map of education entropy (figure 2) helps to shed some light on this result, and shows that high education entropy is concentrated in the suburban area immediately to the west of Philadelphia. This pattern is nearly opposite to that of occupation entropy (figure 2), which suggests that residents in these suburbs have a curious mixture of educational attainments but employment in similar occupational sectors. These suburban areas also tend to have the highest educational attainments in the Philadelphia region—the Pearson correlation at the neighborhood level ($n = 520$) between education entropy and percentage with a high school diploma (over the age of 25) = 0.54 ($p < 0.005$). There are, in fact, very few neighborhoods composed exclusively of highly educated residents: those neighborhoods with high educational attainment also tend to contain many residents with relatively lower educational attainment.

Income entropy was also found to be positively related to neighborhood cooperation and social cohesion. Interestingly, the lowest income entropy scores occur in both the poorest and the wealthiest neighborhoods. Indeed, low variation in household income is the rare characteristic that these two types of neighborhoods share. For instance, figure 3 shows histograms of the percentage of households with incomes above \$60 000, for the neighborhoods in the lowest (a) and highest (b) quartiles of income entropy, respectively.

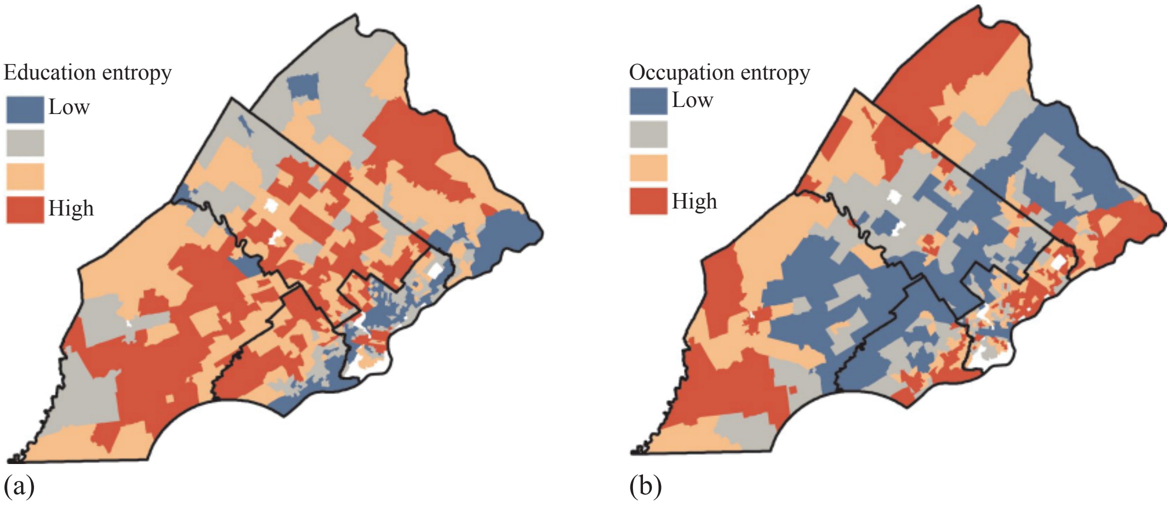

Figure 2. [In color online.] Quantile-classified choropleth maps of education entropy (a) and occupation entropy (b). Each of the four categories (low to high) contains approximately 25% of the neighborhoods.

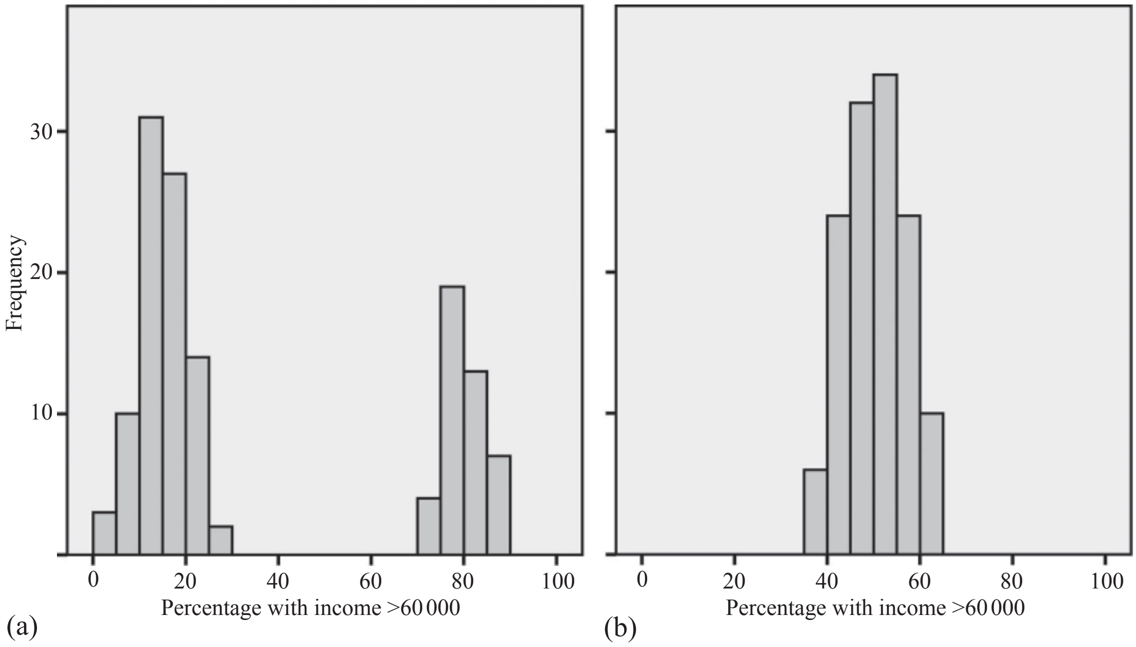

Figure 3. The percentage of the population with annual household incomes greater than $60 000 for those neighborhoods in the lowest (la) and highest (b) quartiles of income entropy. Figure 3(a) shows the top 25% of neighborhoods with the most homogeneous incomes ($n = 130$) and figure 3(b) shows the top 25% of neighborhoods with the most heterogeneous mixture of incomes.

Clearly, low income entropy is associated with extremes of wealth and poverty, whereas high income entropy is associated with household incomes nearer to the average.

While several studies have shown that concentrated disadvantage suppresses neighborhood collective efficacy (Putnam, 2007; Twigg et al, 2010), our results indicate that exclusively wealthy neighborhoods may also engender low collective efficacy, as the residential patterns in these wealthy areas are likely to be composed of large lots which can mitigate casual social interaction with neighbors. Indeed, many exclusively wealthy neighborhoods provide an enclave-like setting, often materialized through fenced-in properties and gated entries, intended as a barrier to community orientation and contact (Grant and Mittelsteadt, 2004; Marcuse, 1997).

Unlike with education and income, it is notable that relatively few neighborhoods in the Philadelphia region have a high degree of ethnic mixing. Indeed, ethnic homogeneity is the norm. Consider, for instance, the histogram of percentage White population by neighborhood (figure 4), which has a bimodal distribution, and shows that most neighborhoods are composed of either mostly White, or mostly non-White, residents. Few neighborhoods lie in the middle of the distribution, where there is a relatively even mixture of White and non-White residents. These patterns, of course, are the result of complicated processes of deindustrialization, suburbanization, and White flight over the past sixty years that have created the dynamic whereby minority ghettos concentrated in inner-city and older regional urbanized areas are separated from majority-White suburban (and, to a lesser extent, urban) enclaves (Adams et al, 1991; Beauregard, 2006).

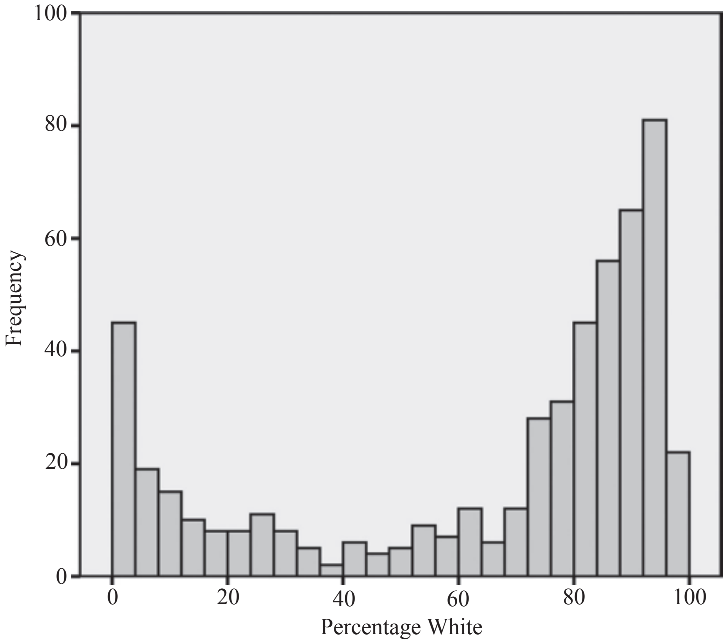

Figure 4. The percentage of the population self-identifying as White (non-Hispanic) by neighborhood ($n = 520$).

A key point from our analysis is that weakened levels of neighborhood collective efficacy are associated with places that exhibit signs of neighborhood transition, or 'churning', characterized by intense neighborhood in-migration and out-migration coupled with increasing levels of diversity. Thus we find that residential mobility and ethnic diversity are negatively associated with neighborhood cooperation and social cohesion. Likewise, other indicators of diversity that are perhaps distinct from socioeconomic class but can signify group cultural norms and identity, such as household type and birthplace, are also associated with weaker collective efficacy. Notably, the Pearson correlations between residential mobility and ethnic, household type, and birthplace entropy are positive and relatively strong ($r = 0.51$, $r = 0.41$, and $r = 0.43$, respectively, all $p < 0.005$).

Education and income diversity, on the other hand, appear to operate in a different fashion from indicators of diversity more closely associated with group cultural norms and identity. Unlike with ethnic diversity, high education and income diversity do not necessarily suggest neighborhood churning: the Pearson correlations of residential mobility with education entropy ($r = 0.13$, $p = 0.01$) and income entropy ($r = 0.02$, $p = 0.66$) are far weaker (and/or not significant) compared with correlations of residential mobility with ethnic, household type, and birthplace entropy. High education entropy, rather, indicates higher neighborhood socioeconomic status, as neighborhoods that are relatively homogeneous in educational attainment tend to be concentrations of low educational attainment. Similarly, the influence of income diversity on collective efficacy likely has little to do with neighborhood churning, as the very wealthiest and very poorest neighborhoods in the region are some of the most resistant to ethnic change. Rather, the positive association of income diversity with collective efficacy reflects the tendency for the wealthiest and poorest neighborhoods in the region both to have low collective efficacy, albeit for very different reasons, where wealth allows for physical and social isolation and poverty restricts the time and energy available for community participation.

6 Conclusion

This research contributes in a number of ways to an understanding of what neighborhood-level factors are associated with collective efficacy. The majority of studies addressing neighborhood collective efficacy have concentrated on the magnitude of neighborhood poverty and, in the few studies incorporating diversity, ethnic diversity has been the focus. In the present study, we found that diversity along a variety of social and economic dimensions besides ethnicity is related to neighborhood collective efficacy. Our analysis also broadens the discussion of neighborhood collective efficacy in the US context to include differences across a metropolitan area, as opposed to the traditional focus on urban neighborhoods. Our results suggest that neighborhood churning, characterized by high levels of diversity in ethnic and other cultural characteristics, and coupled with residential mobility, plays an important role in neighborhood collective efficacy throughout a metropolitan region.

There are several limitations to our analysis. First, methodologically, we created a set of level-2 neighborhood units to better reflect the underlying spatial variation in socioeconomic character. However, we acknowledge there are many ways to tessellate a space into regions, and the impact of the nature of the spatial tessellation on the analytical results is unknown. Also, because this analysis is cross-sectional, we can only speculate upon mechanisms of causation and, thus, distinguish between mechanisms of selection versus influence (Putnam, 2007). Here, although we theorize that diversity influences collective efficacy, it is also likely the case that people who tend toward community mindedness choose to live in (ie, select) certain types of neighborhood. Of course, logic dictates that there is some positive feedback mechanism involved. For instance, a community with strong collective efficacy is likely to attract residents who want to participate in the social life of the community, thus further increasing that neighborhood's stock of social capital (Molotch et al, 2000).

In addition, we have mostly limited our hypotheses to direct effects between each of the neighborhood characteristics and perceptions of collective efficacy. Other researchers have found evidence for indirect effects. For example, the effect of ethnic diversity on neighborhood collective efficacy may be moderated by poverty, where the influence of ethnic diversity on collective efficacy differs depending on the relative level of economic disadvantage of the neighborhood (Sturgis et al, 2010). Or, embedded structural mechanisms, such as concentrated disadvantage, may weaken collective efficacy partially through mediating characteristics such as diversity in ethnicity or other characteristics (Twigg et al, 2010).

There also are a variety of other mechanisms of neighborhood collective efficacy identified in the literature that we have not incorporated into our analysis. For instance, scholars point to the role of formal organizations (Curley 2010), the physical design of neighborhoods (Duany et al, 2000), governmental and economic structures (Bartelt et al, 1987; Van Vliet and Burgers, 1987), and the presence of proactive local leaders (McKnight and Block, 2010; Putnam, 2000) as factors important in creating, nurturing, and implementing collective efficacy. A final limitation to our analysis concerns our focus on a single metropolitan area in the US. We speculate that the relationships between diversity and collective efficacy that we have identified here are similar for other US metropolitan regions, particularly those with similar social and economic histories. However, we acknowledge that local cultural, economic, and related forces may produce different collective efficacy outcomes in different metropolitan regions. Incorporating such local cultural characteristics within a more generalized framework of collective efficacy remains a challenge.

Despite these limitations, our results suggest that the association between diversity and neighborhood collective efficacy is related to a wider range of sociodemographic diversity measures and processes of neighborhood transition than has been identified in past research. We have shown that in southeast Pennsylvania weakened neighborhood collective efficacy is associated with conditions of neighborhood churning. Within this context, ethnic diversity is associated with lower neighborhood collective efficacy—even after accounting for conditions of concentrated disadvantage and residential mobility. Indicators of diversity along dimensions other than ethnicity that can be characterized as representing group cultural norms, such as birthplace and occupation, also have a negative relationship with neighborhood collective efficacy. For indicators that are less tied to cultural norms and identity, such as educational attainment and income, diversity at the neighborhood level is associated with stronger neighborhood collective efficacy.

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