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An Analysis of the Mediating Effects of Social Relations and Controls on Neighborhood Crime Victimization

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Abstract: *Recent tests of systemic social disorganization theory focus on specifying types of informal and formal controls and their ability to mediate the impact of negative structural conditions on neighborhood crime rates. However, a majority of these studies use measures that confound the quality of the relationships needed to develop both informal and formal control with the willingness to exercise these controls. We contribute to this body of literature by making a distinction between the quality of relationships that facilitate the ability to use controls (e.g., social cohesion and police-citizen relations) and the willingness to exercise informal and formal control. Specifically, we test the hypothesis that social cohesion, informal control, police-citizen relations, and formal control differentially mediate the impact that neighborhood structural characteristics have on interpersonal violence and specific types of property crime victimization. Further, we argue that the effects of informal control will be stronger than the effects of formal control, and that the impact of social cohesion and police-citizen relations will be partially mediated by their influence on the exercise of these controls. The results of our hierarchical generalized linear models show that social cohesion, informal control, police-citizen relations, and formal control differentially mediate the impact of neighborhood structural conditions on violent crime and property crime victimization. Our results suggest that strategies needed to prevent violent crime are different than those needed to prevent property crime.*

Keywords: social disorganization, collective efficacy, informal control, formal control, crime, victimization

INTRODUCTION

Since the early 1980s, social disorganization theory has experienced a revitalization in the academic literature. Much of the recent research focuses on extending systemic social disorganization theory by attempting to specify the factors that mediate the impact negative social structural characteristics (e.g., poverty, racial/ethnic heterogeneity, residential mobility) have on neighborhood crime. Most of these studies test the mediating effects of social cohesion, relational ties, attachments, or networks (e.g., Bellair 1997; Lowenkamp, Cullen, and Pratt 2003; Markowitz et al. 2001; Sampson and Groves 1989; Warner and Rountree 1997). More recent research has turned to specifying the sources of informal and/or formal controls (Renauer 2007; Silver and Miller 2004; Triplett, Gainey, and Sun 2003; Wells et al. 2006) and assessing the impact that informal and formal controls have on mediating structural conditions on neighborhood crime rates (Clear et al. 2003; Goudriaan, Wittebrood, and Nieuwbeerta 2006; Sampson, Raudenbush, and Earls 1997; Triplett, Sun, and Gainey 2005; Velez 2001).

Although a growing body of literature has focused on specifying types of informal and formal control and their ability to mediate the impact of negative structural conditions, many of these studies have created measures that focus on either the ability or the willingness of residents to enact control (Triplett et al. 2005). Furthermore, it has been argued that some studies use measures that confound the quality of the relationships that foster the ability to use social controls with the willingness to exercise them (Kubrin and Weitzer 2003; Lowenkamp et al. 2003; Rhineberger-Dunn and Carlson 2009; Triplett et al. 2005). Similarly, a variety of policing-related variables have been used to measure formal control, albeit most confound the issue of relationships between police and neighborhood residents with the exercise of formal control itself (Rhineberger-Dunn and Carlson 2009).

The basic tenets of systemic social disorganization theory suggest that relational variables and control variables should differentially mediate the effects of structural conditions on neighborhood crime rates (Bursik and Grasmick 1993). Relational variables provide for the ability of neighborhood residents to intervene, while control variables reflect their willingness to intervene. Residents will be less willing to intervene if they do not have strong relationships (e.g., cohesion) with each other (Triplett et al. 2005). Furthermore, the effects of informal control should be stronger than the effects of formal control. In neighborhoods where residents are willing to intervene, there should be less reliance on formal control mechanisms, as residents themselves are able to prevent crime from occurring. When residents intervene, it sends a message to other neighborhood residents that serious crime will not be tolerated. This should in turn lead those who want to engage in criminal behavior to take their activities elsewhere if they want to be successful. Lastly, the impact of relational variables should be partially mediated by their influence on the exercise of controls, as relational variables provide for the means to exercise controls. Few studies, however, have addressed these issues.

Our study seeks to build on systemic social disorganization theory by making a distinction between the quality of relationships that facilitate the ability to use controls (e.g., social cohesion and police-citizen relationships) and the willingness to exercise informal and formal control. Specifically, we test the hypothesis that social cohesion, informal control, police-citizen relations, and formal control differentially mediate the impact of structural conditions on neighborhood crime victimization. Further, we argue that the effects of informal control will be stronger than the effects of formal control and that the impact of social cohesion and police-citizen relations will be partially mediated through their influence on the exercise of these controls. In other words, the effect of the social relational variables will be indirect via informal and formal control. We use hierarchical generalized linear modeling to examine the independent effects that social cohesion, informal control, police-citizen relations, and formal control have in mediating the impact of neighborhood structural characteristics on interpersonal violence and specific types of property crime victimization.

THEORETICAL BACKGROUND

Shaw and McKay (1942) developed the original social disorganization theory of crime, emphasizing the effects that local social structural characteristics, such as ethnic heterogeneity and concentrated economic disadvantage, have on crime rates through their negative impact on community dynamics and the ability of a community to regulate itself through the use of informal social controls. Social disorganization theory virtually disappeared from the literature until Kornhauser (1978) addressed the criticisms previously leveled against Shaw and McKay's theory by differentiating the structural and cultural models contained within the original theory, and scholars began integrating Kasarda and Janowitz's (1974) systemic model of community attachment with the structural model of social disorganization.

Kasarda and Janowitz (1974) outlined key components of community dynamics that have since been incorporated into social disorganization models. Specifically, Kasarda and Janowitz's (1974) systemic model of community attachment viewed the local community as a "complex system of friendship and kinship networks and formal and informal associational ties rooted in family life and on-going socialization processes" (Kasarda and Janowitz 1974:329). While their objective was not to develop a theory of crime or explain differences in crime rates across communities, their work had a significant impact on the development of social disorganization theory. During the 1980s and 1990s, a wide variety of studies extended the social disorganization model by specifying the systemic factors that mediate the impact negative social structural characteristics have on neighborhood crime – e.g., social cohesion, ties, attachment, and networks (Bellair 1997; Lowenkamp et al. 2003; Markowitz et al. 2001; Sampson and Groves 1989; Warner and Rountree 1997).

More recent systemic social disorganization research has focused on either specifying factors that influence the level of informal and formal control in a neighborhood (Renauer 2007; Silver and Miller 2004; Triplett et al. 2003; Wells et al. 2006) or on assessing the impact informal and formal control have on mediating the effects of structural conditions on neighborhood crime rates (Clear et al. 2003; Goudriaan et al. 2006; Sampson et al. 1997; Triplett et al. 2005; Velez 2001). The vast majority of the literature on informal control has relied on Sampson et al.'s (1997) concept of collective efficacy, while the majority of research on formal control has focused on a variety of police-related measures, with the most common being satisfaction with police. We turn first to a discussion of informal control.

Informal Control

Shaw and McKay (1942) incorporated the intervening concept of informal control in their seminal work on social disorganization theory. They narrowly defined informal control as related to the supervision and control of teenage peer groups (Shaw and McKay 1942).

Subsequent tests of social disorganization research appear to have integrated three distinct conceptions of informal control. The first follows Shaw and McKay

(1942), with informal control being measured by variables related to unsupervised peer groups (Bellair 2000; Coulton et al. 1999; Lowenkamp, et al. 2003; Sampson and Groves 1989; Sun, Triplett, and Gainey 2004; Veysey and Messner 1999).

The second conception of informal control consists of using measures of social cohesion as indicative of informal control, rather than testing distinct measures of informal control (Bellair 1997; Freudenburg 1986; Markowitz et al. 2001). These studies predict that the higher the level of social cohesion, the more likely it is that informal controls will be used in the neighborhood by residents, thereby decreasing crime.

The majority of the literature, however, has relied on the relatively new conception of informal control that has been added to the systemic social disorganization literature. Specifically, a great number of studies (Bernasco and Block 2009; Feinberg 2006; Kirk 2008; Martin 2002; Morenoff, Sampson, and Raudenbush 2001; Reisig and Cancino 2003; Sampson and Raudenbush 1999; Zhang, Messner, and Liu 2007) have adopted Sampson et al.'s (1997) concept of collective efficacy, that combines measures of social cohesion and informal control into a single index.

Sampson et al. (1997:918) defined collective efficacy as "social cohesion among neighbors combined with their willingness to intervene on behalf of the common good." Essentially, collective efficacy occurs when neighborhood residents have high quality relationships with each other that in turn increases their willingness to use informal controls to prevent crime. Residents' ability to develop collective efficacy differs across neighborhoods, resulting in variations in neighborhood crime rates. Collective efficacy mediates the impact of negative structural conditions on crime, such that the greater the degree of collective efficacy, the lower the crime rate in the neighborhood.

Sampson et al. (1997) used data from the community survey of the Project on Human Development in Chicago Neighborhoods (PHDCN; Earls 1999) collected in 1994-1995, and measures of neighborhood structural characteristics from the 1990 Census to test the hypothesis that collective efficacy mediates the impact of structural conditions on neighborhood crime rates. Sampson et al. (1997) began their analysis with two distinct variables, one for social cohesion/trust and one for informal control. However, these variables were highly correlated (r=0.80). Sampson and his colleagues concluded that these variables tapped the same latent construct and combined them, creating the new variable of collective efficacy. As expected, they found that collective efficacy was lower in neighborhoods with high crime victimization and higher in those with lower crime victimization. They concluded that collective efficacy mediates the impact of structural conditions on neighborhood crime victimization.

Formal Control

The concept of formal control has been inconsistently defined and used in tests of systemic social disorganization theory. It was first conceptualized as neighborhood residents' ability to secure resources (e.g., police) from outside the neighborhood that facilitate the prevention of crime (Bursik and Grasmick 1993). It has also been conceptualized in terms of official criminal justice responses to crime, such as the removal of offenders through arrest and incarceration (Rose and Clear 1998) or "practices of the authorities to maintain order and enforce legal and regulatory codes" (Kubrin and Weitzer 2003:382).

The most common operationalization of formal control in the extant social disorganization literature relies on a broad interpretation of Bursik and Grasmick's (1993) definition. These studies use a composite measure of formal control, with variables measuring residents' perceptions of government and police institutions in their neighborhood. Some measures include local government response to neighborhood issues, satisfaction with police, quality of police services, and police-citizen collaborations (for examples see Renauer 2007; Silver and Miller 2004; Velez 2001).

Silver and Miller (2004) incorporated variables that measure formal control in their attempt to delineate factors influencing neighborhood levels of informal control. Specifically, they included a variable that measures residents' satisfaction with police. Using survey data from the Project on Human Development in Chicago Neighborhoods (PHDCN), Silver and Miller (2004) constructed their police satisfaction concept using Sampson and Jeglum Bartusch's (1998) definition and measurement of the concept. As such, they measured police satisfaction using five variables (with a five-point Likert scale from strongly agree to strongly disagree): the police in this neighborhood are responsive to local issues; the police are doing a good job in dealing with problems that really concern people in this neighborhood; the police are not doing a good job in preventing crime in this neighborhood (reverse coded); the police do a good job in responding to people after they have been victims of crime; and the police are not able to maintain order on the streets and sidewalks in the neighborhood (reverse coded).

Silver and Miller (2004) found that satisfaction with police had a direct, positive, statistically significant impact on informal control, where the higher the satisfaction with police, the higher the level of informal control. Similarly, they also found that satisfaction with police mediates the impact of negative structural conditions on informal control. Disadvantaged neighborhoods had higher levels of informal control if they also had higher levels of satisfaction with police.

Untangling Collective Efficacy and Formal Control

Rhineberger-Dunn and Carlson (2009) argued that both Sampson et al.'s (1997) collective efficacy concept and Silver and Miller's (2004) police satisfaction concept conflate the quality of relationships necessary to develop the ability to utilize informal and formal controls with the exercise of those controls. Specifically, they argued that Sampson et al.'s (1997) collective efficacy concept conflates perceptions of social cohesion and informal control, while Silver and Miller's (2004) police satisfaction concept conflates perceptions of formal control (maintaining order and preventing crime) and police-citizen relations (how well the police respond to problems that are important to people in the neighborhood and to local issues about which residents have concern).

Rhineberger-Dunn and Carlson (2009) conducted two separate confirmatory factor analyses, one of the ten items in the Project on Human Development in Chicago Neighborhoods (PHDCN; Earls 1999) data set used by Sampson et al. (1997) to measure their unidimensional concept of collective efficacy, and another of the five items used by Silver and Miller (2004) to construct their measure of police satisfaction. The results of their confirmatory factor analyses showed that the one-factor model of collective efficacy fit poorly (AGFI=.738, RMSEA=.145), while their final two-factor model fit well (AGFI=.995, RMSEA=.020) in support of their theoretical argument. Similarly, the one-factor police satisfaction model fit poorly (AGFI=.806, RMSEA=.189) compared with their final two-factor model (AGFI=.997, RMSEA=.021) as expected (see Appendix A for all fit measures and factor loadings).

Using hierarchical linear modeling (HLM), the researchers found that neighborhood structural variables differentially impacted perceptions of social cohesion, informal control, police-citizen relations, and formal control. They also found that perceptions of both social cohesion and police-citizen relations mediated the impact of neighborhood structural conditions on perceptions of informal and formal control, respectively. Rhineberger-Dunn and Carlson concluded that if these variables – social cohesion and informal control (i.e., collective efficacy) and police-citizen relations and police effectiveness (i.e., police satisfaction) – are differentially impacted by neighborhood conditions, they may also differentially mediate the impact of these conditions on neighborhood crime victimization.

It is apparent from our review of the more recent systemic social disorganization literature that few studies have provided distinct measures of the quality of relationships (e.g., social cohesion and police satisfaction) needed to foster the ability to use informal and formal controls with the willingness to exercise these controls. Further, few studies have attempted to simultaneously include measures of the quality of relationships and both informal and formal control measures. Those that do tend to test the effects formal control has on the level of informal control in the neighborhood, rather than its ability to differentially mediate the impact of negative structural conditions on neighborhood crime rates.

The purpose of our study is to build on systemic social disorganization theory by making a distinction between the quality of relationships that facilitate the ability to use controls (e.g., social cohesion and police-citizen relationships) and the willingness to exercise informal and formal control. We test the hypothesis that social cohesion, informal control, police-citizen relations, and formal control differentially mediate the impact of structural conditions on neighborhood crime victimization. We further argue that the effects of informal control will be stronger than the effects of formal control, and that the impact of social cohesion and police-citizen relations will be partially mediated by their influence on the exercise of these controls; in other words, the effect of the social relational variables will be indirect via informal and formal control. We test these relationships using hierarchical generalized linear modeling. We turn now to a discussion of the data and measurement of our variables.

DATA AND MEASURES

To test the differential effects perceptions of social cohesion, informal control, police-citizen relations, and formal control have on various types of crime victimization, we use data from the Project on Human Development in Chicago Neighborhoods described earlier (also see Earls 1999). For this survey, 847 census tracts in Chicago were combined to create 343 neighborhood clusters that were constructed to be representative of neighborhoods. Each cluster represents approximately 8,000 people (Sampson et al. 1997). Face-to-face interviews were conducted with 8,782 residents in their homes from the 343 neighborhood clusters included in the study. In addition to basic demographic characteristics (age, race, sex, marital status, mobility, years of residency in the neighborhood, and socioeconomic status), these interviews yielded data on residents' perceptions, attitudes, and participation in their communities (e.g., cohesion among neighbors, participation in local institutions, neighborhood violence, crime victimization). Information on treatment of missing data is given below.

Neighborhood Structural Variables

Neighborhood structural variables were measured using some of the 1990 census measures used in the original Sampson et al. (1997) study.[1] We included four neighborhood structural variables: economic disadvantage, racial heterogeneity, ethnic heterogeneity, and residential stability (see Table 1 for descriptive statistics and Appendix B for bivariate correlations). Our measure of economic disadvantage is based on the factor score derived from a principal components analysis of three 1990 census variables – the percentage unemployed, percentage receiving public assistance, and percentage of the population living below the poverty line.[2]

Much of the social disorganization literature emphasizes that racial-ethnic *heterogeneity* is expected to undermine the degree of social cohesion, as well as the exercise of informal control of crime within neighborhoods. Accordingly, we based our measures on indexes of diversity. We measured racial and ethnic heterogeneity separately to ascertain the differential impacts of these forms of heterogeneity on perceptions of social cohesion, informal control, police-citizen relations, and formal control. Following Sampson and Groves' (1989) work, indexes of diversity were computed for three census variables: percentage Black, percentage Hispanic, and percentage foreign born using the following formula: $D = 1 - \sum p_i^2$, where p_i is the proportion in group *i*. The index of diversity measures the chance that two individuals drawn at random from the neighborhood will come from different racial or ethnic groups. Thus, the first index measured the chance that two randomly-selected individuals would come from different race groups (Black versus not Black), the second the chance that two individuals would come from different ethnic groups (Latino versus not Latino), and the third the chance that two individuals would come from different national origins (foreign born versus not foreign born). Each index takes on a value of 0 when all individuals in the neighborhood come from the same group, and a value of 0.50 when 50 percent fall in each group (i.e., maximum heterogeneity). The Black/not Black index of diversity measures racial heterogeneity, while the factor score derived from the principal components analysis of the Latino/not Latino and foreign born/not foreign born indexes of diversity taps ethnic heterogeneity.

Finally, we follow Sampson and colleagues in using the percentage owner-occupied households and percentage living in the same house as five years prior to the 1990 Census to measure residential stability. Our measure is the factor score derived from a principal components analysis of these two census variables.

Citizen-Level Variables

These individual-level control variables are age (in years), sex (1 if male), Black (1 if Black, 0 for all others), Latino (1 if Latino, 0 for all others), family income (15 categories), education (years of education), three dummy variables for marital status (never married, separated/divorced, and widowed; for all three variables, the reference category is married/domestic partner), number of years lived in the neighborhood (in years), home ownership (1 if own), and mobility (number of times moved in the past five years). See Table 1 for the descriptive statistics of these variables.

Intervening Relations and Control Variables

As discussed above, in our previous research (Rhineberger-Dunn and Carlson 2009), we conducted a confirmatory factor analysis of the ten items in the PHDCN data set that Sampson et al. (1997) used to measure their unidimensional concept of collective efficacy. The results of the confirmatory factor analysis were used to construct weighted factor scores for each of the intervening variables. Social cohesion was measured by four related questions that asked residents how willing people in the neighborhood were to help their neighbors, how strongly they believed the neighborhood was close-knit, their neighbors could be trusted, and if the people in their neighborhood generally did not get along with each other (five-point Likert scales ranging from strongly agree to strongly disagree, last item with reversed polarity). Informal social control was measured by four questions that asked residents how likely they believed their neighbors could be counted on to intervene in such situations as children hanging out on the street while skipping school, children engaged in acts of graffiti, children being disrespectful, and a fight in front of their house (five-point Likert scales ranging from strongly agree to strongly disagree).

Similarly, in our confirmatory factor analysis of police satisfaction, we included the five items used by Silver and Miller (2004). The results of this analysis were used to construct weighted factor scores for the intervening variables. Police-citizen relations was measured by two items that indicate the extent to which neighborhood residents agreed that the police are responsive to local issues and doing a good job responding to problems that concern people in the neighborhood (five-point Likert scales ranging from strongly agree to strongly disagree). Formal control was measured by two items measuring the extent to which citizens feel the police are not doing a good job preventing crime in the neighborhood and are not able to maintain order in the neighborhood (five-point Likert scales ranging from strongly agree to strongly disagree, both items with reversed polarity).

Dependent Variables

We use four types of crime victimization as the dependent variables in our models. Crime victimization is measured by respondents' reports of whether or not anyone in their household had been a victim of interpersonal violence (mugging, fight, or sexual assault), burglary, larceny theft, and/or vandalism within the six months prior to the survey.[3] Understanding the differential effects that social cohesion, informal control, police-citizen relations, and formal control have in mediating the impact that neighborhood structural characteristics have on interpersonal violence and specific types of property crime victimization may lead to better crime control policy initiatives. If a particular type of crime is more affected by social cohesion (closeness and trust with other neighborhood residents), while another is impacted by informal control (a willingness of neighbors to act toward common goals such as controlling neighborhood crime), then preventing each type of crime will require different strategies. For example, neighborhood block parties may be useful for developing recognition and friendship among residents, while neighborhood watch programs might be more effective at increasing informal social control. Therefore, examining the separate effects of these mediating variables on each of these types of crime is necessary to develop better, more effective policies and strategies for reducing and preventing crime in urban neighborhoods.

Table 1. *Descriptive Statistics for Neighborhood-level and Citizen-level Variables*

Variable	Mean	Standard Deviation	Minimum	Maximum
Neighborhood-level				
Economic disadvantage	.000	1.000	-1.180	4.327
Residential stability	.000	1.000	-2.068	2.326
Ethnic heterogeneity	.000	1.000	-1.235	1.752
Racial heterogeneity	.104	.138	.000	.500
Social cohesion	-.371	.175	-.747	.300
Police-citizen relations	-.423	.174	-.973	.162
Informal control	-.189	.210	-.913	.551
Formal control	-.246	.152	-.665	.140
Citizen-level				
Age	42.698	16.828	17	100
Years of education	12.374	3.068	1	17
Male (=1)	.408	.492	0	1
Black (=1)	.400	.491	0	1
Latino (=1)	.250	.433	0	1
Family income	5.830	3.516	1	15
Separated/divorced (=1)	.163	.370	0	1
Widowed (=1)	.098	.298	0	1
Never married (=1)	.315	.464	0	1
Years in neighborhood	12.261	13.190	0	91
Homeowner (=1)	.455	.498	0	1
Moves past 5 years	.945	1.389	0	11
Violent crime victimization	.051	.220	0	1
Burglary victimization	.035	.184	0	1
Larceny victimization	.126	.332	0	1
Vandalism victimization	.149	.356	0	1

Missing Data

Many variables in the PHDCN data set contained missing data. Use of listwise deletion of missing data would have resulted in a loss of over two-thirds of the cases in our hierarchical crime victimization models and over 40 percent of the cases in our level-1 models. Due to differences in levels of measurement and amounts of missing data, we adopted two strategies for dealing with the missing data in our analyses in the present study.[4]

First, to impute the missing values of the level-1 socio-demographic variables, we used SAS PROC MI with the BY option (random seed 1962), which allowed us to impute values within neighborhoods in order to preserve the distribution of within neighborhood composition, following the procedures detailed by Allison (2002:27-41). SAS PROC MI uses the multivariate data augmentation algorithm detailed in Schafer (1997:181-192). The imputation model included only the socio-demographic citizen-level variables. While some authors (Allison 2002; Schafer and Graham 2002) make a strong argument for using all variables to be analyzed in the imputation model, including the continuous dependent variable(s), they are silent as to whether dichotomous dependent variables (as the ones here) should be included, as well as ordered categorical variables (as are the collective efficacy and police satisfaction items). Accordingly, we limited our imputation model to the socio-demographic variables.

Second, the crime victimization dependent variables contain very few missing cases (less than one percent). Schafer (1997:1) suggests that when five percent or fewer of the cases are missing, listwise deletion of missing cases "may be a perfectly reasonable solution to the missing-data problem." Following this advice, we used listwise deletion of cases that had missing values on the crime victimization variables.

Hierarchical Generalized Linear Models

We used logistic regression in our crime victimization models because the crime victimization items are dichotomous variables. Dichotomous dependent variables violate the assumptions of normality and linearity that underlie hierarchical linear modeling. Bernoulli models with overdispersion were estimated using PQL estimation. We report the results for population average models with robust standard errors.[5] The level-1, individual-level model controls for response bias and neighborhood composition using the 12 socio-demographic variables. These level-1 models take the following form:

$$\eta_{ij} = \beta_{0j} + \sum_{p=1}^{12} \beta_{pj} X_{pij} + r_{ij},$$

where η_{ij} is the log odds of crime victimization, β_{0j} is the model intercept, X_{pij} is socio-demographic characteristic p for person i in neighborhood j, β_{pj}'s are partial logistic regression coefficients, and r_{ij} is the random individual effect.

The level-2, neighborhood-level model predicts the neighborhood log odds of crime victimization using neighborhood structural characteristics and relations and control variables. These models have the following form:

$$\beta_{0j} = \gamma_{p0} + \sum_{s=1}^{S_p} \gamma_{ps} W_{sj} + u_{pj},$$

where β_{0j} is the log odds of neighborhood crime victimization adjusted for level-one variables, γ_{p0} is the model intercept, W_{sj} is neighborhood structural characteristic s for neighborhood j, γ_{ps}'s are partial logistic regression coefficients, and u_{pj} is the level-2 random effect.

For each dependent variable, the first model estimated was the unconditional means model as described above to obtain the variance partition coefficient (i.e., the ICC for generalized linear models with overdispersion) using the latent variable approach in Browne et al. (2005:604). Then, the next model estimated included the level-1 predictors. The third model added the neighborhood structural characteristics to obtain the total effects of these variables on crime victimization. The fourth model examined the mediating effects of perceptions of social cohesion and police-citizen relations. The fifth model examined the mediating effects of perceived informal and formal control.

The final model included the mediating effects of all intervening variables. Some tests of social disorganization have encountered excessively high levels of multicollinearity among neighborhood structural characteristic measures (e.g., Snell 2001). In addition, Sampson et al. (1997) found that social cohesion and informal control were highly correlated once aggregated to the neighborhood level. As Appendix B shows, our measures of social cohesion and informal control are highly correlated (r = .839), as are police-citizen relations and formal control (r = .855), although as our confirmatory factor analysis indicates, these are distinct variables. The only model where multicollinearity poses a potential problem is the one containing all of the intervening variables, where tolerance statistics for the intervening variables ranged from .226 to .289 and variance inflation factors from 3.460 to 4.427. However, the numerical solution is stable and our null findings are not due to inflated standard errors, thus giving us confidence in the veracity of our results.[6]

FINDINGS

Table 2 presents the results of our hierarchical generalized linear models of violent crime victimization. The unconditional means model[7] shows that 37.4 percent of the overall variation in this type of victimization is between neighborhoods (p = .000). The first model (individual-level model) in Table 2 displays the effects of neighborhood composition on neighborhood violent crime victimization. Being Black increases the odds of violent crime victimization by 40.5%, being Latino increases the odds by 29.2%, being separated/divorced increases the odds by 33.0%, while being a homeowner decreases the odds of violent crime victimization by 20.5%. In addition, increases in income and age significantly reduce the chances of violent crime victimization. Differences in neighborhood composition explain 30.4% of the variation in violent crime victimization between neighborhoods.

***Table 2**. HGLM Models of Violent Crime Victimization: Logit Coefficients, (Standard Error Estimates), and Odds Ratios*

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Intercept	-2.032 (.350)**	-2.252 (.357)**	-3.295 (.400)**	-2.841 (.381)**	-3.134 (.392)**
	.131	*.105*	*.037*	*.058*	*.044*
Neighborhood Level (n=343)					
Economic disadvantage	---	.303 (.067)**	.119 (.072)*	.119 (.071)*	.107 (.072)
		1.354	*1.126*	*1.127*	*1.113*
Racial heterogeneity	---	-.966 (.407)**	-1.064 (.407)**	-1.082 (.406)**	-1.110 (.422)**
		.381	*.345*	*.339*	*.329*
Ethnic heterogeneity	---	.331 (.081)**	.258 (.085)**	.257 (.083)**	.254 (.084)**
		1.393	*1.294*	*1.293*	*1.290*
Residential stability	---	.001 (.069)	.060 (.069)	.081 (.070)	.081 (.070)
		1.001	*1.062*	*1.084*	*1.085*
Social cohesion	---	---	-1.473 (.372)**	---	-.908 (.462)*
			.229		*.403*
Police-citizen relations	---	---	-1.013 (.346)**	---	-.390 (.651)
			.363		*.677*
Informal control	---	---	---	-1.296 (.327)**	-.711 (.380)*
				.274	*.491*
Formal control	---	---	---	-1.079 (.428)**	-.663 (.764)
				.340	*.515*
Citizen Level (n=8,562)					
Years in neighborhood	.004 (.004)	.003 (.004)	.003 (.004)	.003 (.004)	.003 (.004)
	1.004	*1.003*	*1.003*	*1.003*	*1.003*
Black	.340 (.132)**	.410 (.145)**	.368 (.148)**	.356 (.146)**	.357 (.148)**
	1.405	*1.507*	*1.444*	*1.428*	*1.429*
Moves past 5 years	.044 (.036)	.046 (.036)	.044 (.037)	.047 (.036)	.046 (.037)
	1.045	*1.047*	*1.045*	*1.048*	*1.047*
Family income	-.052 (.019)**	-.037 (.020)*	-.035 (.020)*	-.034 (.020)	-.034 (.020)*
	.950	*.963*	*.965*	*.966*	*.966*
Age	-.014 (.004)**	-.012 (.004)**	-.012 (.004)**	-.012 (.004)**	-.012 (.004)**
	.987	*.988*	*.988*	*.988*	*.988*
Years education	-.026 (.018)	-.016 (.018)	-.012 (.019)	-.012 (.018)	-.012 (.018)
	.974	*.984*	*.988*	*.988*	*.988*
Never married	-.023 (.123)	-.025 (.125)	-.017 (.127)	-.014 (.126)	-.014 (.127)
	.977	*.976*	*.983*	*.986*	*.986*
Separated/divorced	.285 (.131)*	.282 (.133)*	.282 (.135)*	.278 (.134)*	.280 (.135)*
	1.330	*1.326*	*1.326*	*1.321*	*1.323*
Widowed	-.301 (.214)	-.282 (.218)	.273 (.226)	-.278 (.224)	-.276 (.225)
	.740	*.754*	*.761*	*.757*	*.759*
Male	.013 (.091)	.013 (.092)	.013 (.095)	.006 (.094)	.010 (.095)
	1.013	*1.013*	*1.013*	*1.007*	*1.010*
Latino	.256 (.150)*	.139 (.155)	.062 (.159)	.047 (.160)	.046 (.160)
	1.292	*1.149*	*1.064*	*1.048*	*1.047*
Homeowner	-.230 (.112)*	-.157 (.115)	-.178 (.118)	-.171 (.117)	-.176 (.118)
	.795	*.855*	*.837*	*.843*	*.838*
Neighborhood Variance Explained:					
Citizen-level variables	30.4%	30.4%	30.4%	30.4%	30.4%
Neighborhood-level variables	--	9.6%	29.3%	26.5%	28.8%
Total explained	30.4%	40.0%	59.7%	56.9%	59.2%

$^{*}p \leq .05$; $^{**}p \leq .01$ (one-tailed tests)

Model 2 reveals that both economic disadvantage and ethnic heterogeneity are positively and significantly related to violent crime victimization, while racial heterogeneity has a statistically significant dampening effect on violent crime victimization. Model 3 shows that when the social cohesion and police-citizen relations perception variables are added to the model, they are both statistically significant, in a negative direction, and the effect of economic disadvantage on violent crime victimization decreases by more than half. We see similar results in Model 4 when perceptions of informal control and formal control are added to the model. Both perceived informal control and formal control have dampening effects on violent crime victimization, and the effect of economic disadvantage substantially decreases.

Lastly, when all four intervening variables are added to the model (Model 5), social cohesion and informal control are significantly and negatively related to the neighborhood structural variables, while perceived police-citizen relations and formal control are no longer statistically significant. Additionally, economic disadvantage drops to nonsignificance. This indicates that social cohesion and informal control mediate the impact of structural characteristics on violent crime victimization. Even in neighborhoods characterized by high levels of economic disadvantage, violence may be lower if residents perceive social cohesion in their neighborhood to be high and that residents are willing to intervene to prevent crime and delinquency. This model explains 59.2% of the variation in violent crime victimization across neighborhoods.

Turning to burglary victimization (see Table 3), the unconditional means model shows that 34.1% of the variation in burglary victimization exists between neighborhoods (p = .000). Model 1 (individual-level model) indicates that three citizen-level variables significantly influence burglary victimization. Being Latino increases the chances of burglary victimization by 62.2%, while the number of moves significantly increases and age decreases the odds of this type of victimization. Differences in neighborhood composition explain 35.4% of the variation in burglary victimization across neighborhoods.

The remaining models in Table 3 show that the results for burglary victimization differ substantially from those discussed for violent crime victimization. In the second model, economic disadvantage and ethnic heterogeneity are positively and significantly related to burglary victimization, while residential stability significantly decreases such victimization, and racial heterogeneity is nonsignificant. The third model reveals that when the social cohesion and police-citizen relations perception variables are added to the model, residential stability is the only neighborhood structural characteristic to significantly affect burglary victimization. Economic disadvantage and ethnic heterogeneity drop to nonsignificance. When the informal control and formal control variables are added to the model (Model 4), the pattern of significant structural variables changes, with racial heterogeneity now having a statistically significant and negative impact on burglary victimization. Residential stability retains its negative, statistically significant relationship with this type of victimization. Additionally, perceptions of formal control decrease the probability of burglary victimization, while informal control has no significant effect.

Lastly, in Model 5, when all four intervening variables are added to the model, two structural variables statistically and negatively impact burglary victimization. Both racial heterogeneity and residential stability decrease burglary victimization. When all four intervening variables are added to the model, police-citizen relations drops to nonsignificance, while formal control retains its negative, statistically significant impact on burglary victimization. Burglary victimization is lower in neighborhoods that are more racially diverse, have more stable populations, and where residents indicate the police are doing a good job of maintaining order and preventing crime in the neighborhood. This model explains 59.9% of the variation in burglary victimization across neighborhoods.

The full-model (Model 5) results for burglary victimization contrast significantly with the full-model results for violent victimization. While racial heterogeneity is significantly related to both violent crime and burglary victimization, ethnic heterogeneity is only significantly related to violent crime victimization. More importantly, social cohesion and informal control mediate the impact of structural characteristics on violent crime victimization, but do not do so for burglary victimization. In contrast, formal control mediates the impact of structural characteristics on burglary victimization, but not violent crime victimization.

***Table 3**. HGLM Models of Burglary Victimization: Logit Coefficients, (Standard Error Estimates), and Odds Ratios*

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Intercept	-3.135 (.365)**	-3.354 (.375)**	-3.960 (.430)**	-3.805 (.400)**	-3.840 (.429)**
	.044	*.035*	*.019*	*.022*	*.021*
Neighborhood Level (n=343)					
Economic disadvantage	---	.251 (.083)**	.116 (.104)	.107 (.101)	.106 (.105)
		1.285	*1.123*	*1.113*	*1.112*
Racial heterogeneity	---	-.688 (.441)	-.661 (.437)	-.774 (.444)*	-.767 (.436)*
		.502	*.516*	*.461*	*.464*
Ethnic heterogeneity	---	.198 (.086)*	.131 (.091)	.122 (.092)	.120 (.091)
		1.219	*1.140*	*1.129*	*1.128*
Residential stability	---	-.214 (.088)**	-.198 (.088)*	-.185 (.090)*	-.186 (.090)*
		.807	*.821*	*.831*	*.830*
Social cohesion	---	---	-.364 (.442)	---	-.078 (.511)
			.695		*.925*
Police-citizen relations	---	---	-1.042 (.405)**	---	-.087 (.670)
			.353		*.917*
Informal control	---	---	---	-.368 (.435)	-.310 (.478)
				.692	*.734*
Formal control	---	---	---	-1.363 (.490)**	-1.281 (.769)*
				.256	*.278*
Citizen Level (n=8,562)					
Years in neighborhood	-.003 (.005)	-.004 (.005)	-.003 (.005)	-.003 (.005)	-.003 (.005)
	.997	*.996*	*.997*	*.997*	*.997*
Black	.129 (.143)	.143 (.175)	.122 (.180)	.097 (.177)	.096 (.177)
	1.138	*1.153*	*1.130*	*1.102*	*1.101*
Moves past 5 years	.080 (.040)*	.075 (.040)*	.074 (.041)*	.076 (.041)*	.076 (.041)*
	1.084	*1.077*	*1.077*	*1.079*	*1.078*
Family income	-.005 (.026)	.012 (.026)	.013 (.027)	.015 (.026)	.015 (.026)
	.995	*1.012*	*1.013*	*1.015*	*1.015*
Age	-.007 (.005)*	-.007 (.005)	-.007 (.005)	-.006 (.005)	-.006 (.005)
	.993	*.993*	*.993*	*.994*	*.994*
Years education	-.020 (.022)	-.014 (.023)	-.012 (.023)	-.010 (.023)	-.010 (.023)
	.980	*.986*	*.988*	*.990*	*.990*
Never married	.207 (.141)	.188 (.143)	.185 (.147)	.190 (.146)	.190 (.145)
	1.230	*1.207*	*1.203*	*1.209*	*1.209*
Separated/divorced	.232 (.170)	.224 (.171)	.213 (.176)	.214 (.175)	.215 (.174)
	1.261	*1.251*	*1.238*	*1.238*	*1.240*
Widowed	.195 (.237)	.212 (.243)	.212 (.249)	.211 (.247)	.212 (.246)
	1.215	*1.236*	*1.236*	*1.235*	*1.236*
Male	-.092 (.114)	-.103 (.116)	-.108 (.119)	-.114 (.119)	-.113 (.118)
	.912	*.902*	*.897*	*.893*	*.893*
Latino	.483 (.148)**	.373 (.151)**	.333 (.160)*	.311 (.160)*	.309 (.159)*
	1.622	*1.451*	*1.396*	*1.365*	*1.362*
Homeowner	.145 (.151)	.292 (.157)*	.280 (.161)*	.283 (.159)*	.282 (.159)*
	1.156	*1.340*	*1.323*	*1.327*	*1.326*
Neighborhood Variance Explained:					
Citizen-level variables	35.4%	35.4%	35.4%	35.4%	35.4%
Neighborhood-level variables	--	10.0%	29.4%	27.8%	24.5%
Total explained	35.4%	45.4%	64.8%	63.2%	59.9%

$^{*}p \leq .05$; $^{**}p \leq .01$ (one-tailed tests)

Table 4 presents the results of our hierarchical linear models for larceny victimization. The unconditional means model indicates that 20.7% of the variation in larceny victimization is between neighborhoods (p = .000). Model 1 (individual-level model) in Table 4 indicates that four variables have significant effects on the odds of larceny victimization. Being a homeowner increases the odds of larceny crime victimization by 62.2% and being Latino increases these odds by 27.4%. Moreover, the number of moves in the past five years significantly increases the

Table 4*. HGLM Models of Larceny Victimization: Logit Coefficients, (Standard Error Estimates), and Odds Ratios*

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Intercept	-1.669 (.228)**	-1.996 (.235)**	-2.429 (.266)**	-2.405 (.247)**	-2.203 (.274)**
	.188	*.136*	*.088*	*.090*	*.110*
Neighborhood Level (n=343)					
Economic disadvantage	---	.346 (.059)**	.230 (.064)**	.201 (.062)**	.208 (.063)**
		1.414	*1.259*	*1.223*	*1.231*
Racial heterogeneity	---	-.005 (.280)	.093 (.294)	-.049(.293)	-.035 (.298)
		.995	*1.097*	*.952*	*.966*
Ethnic heterogeneity	---	.369 (.061)**	.311 (.062)**	.294 (.061)**	.297 (.061)**
		1.446	*1.364*	*1.341*	*1.345*
Residential stability	---	-.009 (.050)	-.015 (.054)	.009 (.053)	.007 (.053)
		.991	*.985*	*1.009*	*1.007*
Social cohesion	---	---	.108 (.286)	---	.700 (.368)*
			1.115		*2.015*
Police-citizen relations	---	---	-1.092 (.288)**	---	.212 (.518)
			.335		*1.236*
Informal control	---	---	---	-.248 (.239)	-.698 (.317)*
				.781	*.497*
Formal control	---	---	---	-1.401 (.318)**	-1.652 (.564)**
				.246	*.192*
Citizen Level (n=8,562)					
Years in neighborhood	.003 (.003)	.003 (.003)	.003 (.003)	.003 (.003)	.003 (.003)
	1.003	*1.003*	*1.003*	*1.003*	*1.003*
Black	.092 (.088)	.156 (.108)	.135 (.107)	.105 (.107)	.105 (.107)
	1.096	*1.169*	*1.145*	*1.110*	*1.111*
Moves past 5 years	.068 (.024)**	.068 (.024)**	.068 (.024)**	.069 (.024)**	.070 (.024)**
	1.070	*1.070*	*1.070*	*1.072*	*1.073*
Family income	.016 (.012)	.032 (.012)**	.033 (.013)**	.035 (.013)**	.035 (.013)**
	1.016	*1.032*	*1.033*	*1.036*	*1.035*
Age	-.016 (.003)**	-.015 (.003)**	-.015 (.003)**	-.015 (.003)**	-.015 (.003)**
	.984	*.985*	*.985*	*.985*	*.985*
Years education	-.007 (.014)	.001 (.013)	.002 (.013)	.003 (.013)	.003 (.013)
	.993	*1.001*	*1.002*	*1.003*	*1.003*
Never married	-.131 (.082)	-.134 (.082)	-.136 (.082)*	-.134 (.083)	-.133 (.083)
	.877	*.875*	*.873*	*.875*	*.876*
Separated/divorced	.154 (.097)	.138 (.098)	.134 (.098)	.133 (.098)	.133 (.098)
	1.167	*1.148*	*1.143*	*1.142*	*1.142*
Widowed	.018 (.150)	.035 (.154)	.034 (.154)	.032 (.155)	.032 (.154)
	1.018	*1.036*	*1.034*	*1.033*	*1.033*
Male	-.034 (.069)	-.047 (.070)	-.052 (.070)	-.056 (.071)	-.058 (.071)
	.966	*.954*	*.950*	*.946*	*.944*
Latino	.242 (.093)**	.097 (.092)	.063 (.093)	.035 (.092)	.036 (.092)
	1.274	*1.102*	*1.065*	*1.035*	*1.037*
Homeowner	.484 (.077)**	.568 (.080)**	.564 (.081)**	.564 (.080)**	.569 (.081)**
	1.622	*1.766*	*1.758*	*1.758*	*1.766*
Neighborhood Variance Explained:					
Citizen-level variables	0%	0%	0%	0%	0%
Neighborhood-level variables	--	35.3%	38.7%	44.0%	43.8%
Total explained	0%	35.3%	38.7%	44.0%	43.8%

$^{*}p \le .05$; $^{**}p \le .01$ (one-tailed tests) probability of larceny victimization while age decreases the odds of this type of victimization. This model explains none (0.00%) of the variation in larceny victimization between neighborhoods.

Model 2 reveals that two neighborhood structural variables are significantly related to larceny victimization. Both economic disadvantage and ethnic heterogeneity significantly increase the probability of larceny victimization. Turning to the third model in Table 4, we see that these two neighborhood structural variables continue to exert a positive, significant impact on larceny victimization, yet their effects are reduced once social cohesion and police-citizen relations are added to the model. Additionally, police-citizen relations has a negative, statistically significant impact on larceny victimization. When informal control and formal control are entered as mediating variables (Model 4), formal control is statistically significant and has a negative effect on larceny victimization. Economic disadvantage and ethnic heterogeneity retain their positive, statistically significant effects but have less impact on this type of victimization.

Lastly, Model 5 shows that perceptions of both informal and formal control have a negative and statistically significant relationship with larceny victimization. Interestingly, social cohesion has an unexpected positive, statistically significant relationship with larceny victimization. Cohesive neighborhoods may have a significant overlapping of family, friend, and criminal networks, resulting in a tolerance for minor types of crime such as larceny (Patillo 1998). Although residents trust their neighbors because they are family and friends, some of these individuals are criminal, which may unwittingly make them targets of petty crime. Economic disadvantage and ethnic heterogeneity retain their positive, statistically significant impact on larceny victimization, while police-citizen relations drops to nonsignificance. This model explains 43.8% of the variation in larceny victimization across neighborhoods.

The results for larceny victimization are more similar to violent crime victimization than to burglary victimization. As with violent crime victimization, ethnic heterogeneity is significantly related to larceny victimization. Additionally, as with violent crime victimization, social cohesion and informal control mediate the impact of structural characteristics on larceny crime victimization. Finally, as with burglary victimization, formal control significantly mediates the impact of structural characteristics on larceny victimization.

The unconditional means model for vandalism victimization shows that 17.4% of the total variation exists across neighborhoods (p = .000). Model 1 (individual-level model) in Table 5 indicates that five variables have a significant impact on the odds of vandalism victimization. Being Latino increases the odds of vandalism victimization by 36.8%, while being widowed decreases the odds by 19.7%, and never being married decreases the odds by 17.7%. In addition, increases in family income and number of moves in the past five years increase the odds of vandalism victimization. Differences in neighborhood composition explain 27.4% of the variation in vandalism victimization across neighborhoods.

Model 2 shows that both economic disadvantage and ethnic heterogeneity have a positive and statistically significant impact on vandalism victimization. However, when the social cohesion and police-citizen relations variables are added (Model 3), ethnic heterogeneity is the only structural variable that remains significant. This model also reveals that while police-citizen relations has a negative, statistically significant impact on vandalism victimization, social cohesion is not significantly related to this type of victimization.

The fourth model in Table 5 reveals that both informal control and formal control are statistically significant and that both decrease vandalism victimization. Ethnic heterogeneity remains the only statistically significant structural variable. When all four intervening variables are added to the model (Model 5), only informal control and formal control are significant, and both are negatively related to vandalism victimization. Ethnic heterogeneity is the only statistically significant structural variable. These results indicate that both informal control and formal control mediate the impact of negative structural conditions on vandalism victimization. As was the case with burglary and larceny victimization, neither social cohesion nor police-citizen relations significantly affect vandalism victimization, and police-citizen relations drops to nonsignificance when informal control and formal control are added to the model. This model explains 57.3% of the variation in vandalism victimization across neighborhoods.

The results for vandalism victimization are more similar to larceny victimization than violent crime victimization and are strikingly different from burglary victimization. Similar to larceny and violent crime victimization, ethnic heterogeneity is significantly related to vandalism victimization. Additionally, both informal and formal control significantly mediate the impact of structural characteristics on vandalism victimization, as they do for larceny victimization. However, there are no similar significant relationships between larceny and burglary.

***Table 5**. HGLM Models of Vandalism Victimization: Logit Coefficients, (Standard Error Estimates), and Odds Ratios*

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Intercept	-1.517 (.222)**	-1.690 (.232)**	-2.167 (.258)**	-2.068 (.241)**	-1.964 (.269)**
	.219	*.184*	*.115*	*.126*	*.140*
Neighborhood Level (n=343)					
Economic disadvantage	---	.182 (.047)**	.060 (.058)	.042 (.057)	.040 (.058)
		1.200	*1.061*	*1.043*	*1.041*
Racial heterogeneity	---	-.329 (.229)	-.248 (.237)	-.367(.232)	-.320 (.251)
		.719	*.780*	*.693*	*.726*
Ethnic heterogeneity	---	.219 (.051)**	.160 (.054)**	.150 (.054)**	.148 (.054)**
		1.245	*1.173*	*1.161*	*1.160*
Residential stability	---	-.076 (.050)	-.074 (.049)	-.047 (.048)	-.053 (.048)
		.926	*.929*	*.954*	*.948*
Social cohesion	---	---	-.073 (.299)	---	.548 (.400)
			.930		*1.729*
Police-citizen relations	---	---	-1.023 (.309)**	---	-.125 (.500)
			.359		*.882*
Informal control	---	---	---	-.447 (.259)*	-.749 (.345)*
				.639	*.473*
Formal control	---	---	---	-1.086 (.314)**	-1.037 (.528)*
				.338	*.354*
Citizen Level (n=8,562)					
Years in neighborhood	.004 (.003)	.004 (.003)	.004 (.003)	.004 (.003)	.004 (.003)
	1.004	*1.004*	*1.004*	*1.004*	*1.004*
Black	-.136 (.077)*	-.067 (.092)	-.091 (.090)	-.117 (.090)	-.112 (.090)
	.873	*.935*	*.913*	*.890*	*.894*
Moves past 5 years	.059 (.023)**	.056 (.023)**	.056 (.023)**	.057 (.023)**	.058 (.023)**
	1.060	*1.057*	*1.057*	*1.059*	*1.059*
Family income	.033 (.014)*	.044 (.014)**	.045 (.014)**	.047 (.014)**	.047 (.014)**
	1.034	*1.045*	*1.046*	*1.048*	*1.048*
Age	-.017 (.003)**	-.017 (.003)**	-.017 (.003)**	-.017 (.003)**	-.017 (.003)**
	.983	*.984*	*.983*	*.984*	*.984*
Years education	.014 (.011)	.019 (.011)*	.021 (.011)*	.022 (.011)*	.022 (.011)*
	1.015	*1.019*	*1.021*	*1.022*	*1.022*
Never married	-.195 (.077)**	-.198 (.077)**	-.198 (.076)**	-.195 (.076)**	-.195 (.077)**
	.823	*.821*	*.820*	*.823*	*.823*
Separated/divorced	.063 (.094)	.054 (.095)	.051 (.095)	.050 (.095)	.049 (.095)
	1.065	*1.056*	*1.052*	*1.052*	*1.050*
Widowed	-.219 (.142)	-.206 (.144)	-.208 (.144)	-.210 (.144)	-.211 (.145)
	.803	*.814*	*.812*	*.810*	*.810*
Male	.011 (.062)	.000 (.062)	-.003 (.062)	-.007 (.063)	-.007 (.063)
	1.011	*1.000*	*.997*	*.993*	*.993*
Latino	.313 (.089)**	.212 (.091)**	.175 (.090)*	.156 (.089)*	.159 (.089)*
	1.368	*1.237*	*1.192*	*1.169*	*1.172*
Homeowner	.053 (.075)	.128 (.079)	.122 (.079)	.123 (.079)	.126 (.079)
	1.055	*1.136*	*1.130*	*1.130*	*1.134*
Neighborhood Variance Explained:					
Citizen-level variables	27.4%	27.4%	27.4%	27.4%	27.4%
Neighborhood-level variables	--	15.6%	22.2%	27.5%	29.9%
Total explained	27.4%	43.0%	49.6%	54.9%	57.3%

$^{*}p \le .05$; $^{**}p \le .01$ (one-tailed tests)

DISCUSSION

Theoretical and Research Implications

The HLM results provide ample evidence to support our theoretical claim of the importance of distinguishing between the relationships that provide for the ability of neighborhood residents to use controls and the willingness to exercise these controls. Specifically, we found that social cohesion, informal control, police-citizen relations, and formal control differentially mediate the effects of neighborhood structural variables. Economic disadvantage has a direct impact on burglary and vandalism victimization. However, when the intervening variables are added to the model, it becomes nonsignificant. Similarly, economic disadvantage has a direct impact on violent crime victimization, but its effect becomes smaller when the intervening variables are added and drops to nonsignificance when all four intervening variables are in the final model. Additionally, the effect of residential stability on burglary drops substantially when these variables are entered into the model.

The pattern of results involving our separate racial and ethnic heterogeneity variables has direct implications for systemic social disorganization theory. Ethnic heterogeneity clearly impacts both the intervening and the crime victimization variables differently than racial heterogeneity. Ethnic heterogeneity has a direct, statistically significant, and positive impact on all victimization variables except burglary victimization. Racial heterogeneity, however, has a statistically significant, negative impact on only two variables – violent victimization and burglary victimization. However, it does not have a statistically significant impact on the odds of burglary victimization until after the mediating variables have been added to the model.

The fact that racial heterogeneity has a negative impact and that it does not influence all four types of crime victimization contradicts Shaw and McKay's assertion that racial diversity increases crime in the neighborhood. Our results suggest that the more racially diverse the neighborhood, the lower the violent crime victimization and that neighborhoods with higher racial diversity will have lower odds of burglary victimization holding constant levels of social cohesion, police-citizen relations, informal control, and formal control. Rather, our results support Sampson and Wilson's (1995) assertion that crime is lower in neighborhoods where there is more contact among groups of different races and less social isolation (i.e., residents have more contact with mainstream social networks and positive role models). In racially heterogeneous neighborhoods, residents are exposed to mainstream cultural constructions of violence and its appropriate/inappropriate use, which should lead to lower odds of serious crimes such as violence and burglary. These results suggest the need for future research to include distinct measures of racial and ethnic heterogeneity in order to assess their differential impact on crime victimization.

Our results do not support our argument that the effects of informal control will be stronger than the effects of formal control. Informal control has a stronger impact than formal control on violent crime victimization. However, for all three types of property crime victimization, formal control has a stronger effect than informal control. Our results may be explained in part by a hybrid form of control that reflects the interdependency of informal and formal control, or what Carr (2003) identifies as the "new parochialism." With this type of control, residents do not directly intervene to prevent crime in the neighborhood. Rather, they intervene indirectly by mobilizing mechanisms of formal control by calling the police or other outside agencies to deal with the problem (e.g., petitioning the liquor commission to deny the renewal of a local bar's liquor license) (Carr 2003). Applied to our study findings, neighborhood residents may be more willing to call the police when they see a burglary, vandalism, or larceny in progress, perhaps out of fear of encountering an unknown offender or because they believe the police are better equipped to handle these crimes. Residents may be more likely to personally intervene in violent crime, perhaps because they are more likely to know the victim and/or offender, and may therefore be less willing to see those offenders arrested. In any case, our results suggest significantly different policy implications for the control of violent and property crime.

Our results do, however, support our argument that the impact of social cohesion and police-citizen relations are partially mediated by their influence on the exercise of informal and formal controls, respectively. Social cohesion is significant for violent crime and larceny victimization. While social cohesion does have a direct effect on violent crime victimization, its effects are partially mediated by its impact on informal control. Police-citizen relations has a significant impact on all four types of victimization when it is alone in the model with the neighborhood structural variables (see model 3 in each table). However, in every case it drops to nonsignificance in the full model. For burglary, the effect of police-citizen relations is partially mediated by its influence on formal control. For both larceny and vandalism, the effect of police-citizen relations is completely mediated by its influence on both informal and formal control. These results suggest that future research should consider including distinct measures of social cohesion, informal control, police-citizen relations, and formal control as intervening variables in the systemic social disorganization model.

Policy Implications

Our results also have important implications for crime policies aimed at reducing and preventing neighborhood-level crime victimization. The pattern of intervening effects related to violent crime victimization differs substantially from the three types of property crime victimization. Social cohesion is significant in the final model (Model 5) for violent crime victimization and the final model for larceny victimization, while formal control is significant in every final model except violent crime victimization. These results suggest different approaches are needed for the prevention and reduction of violent crimes compared to property crimes. First, programs or activities designed to increase neighborhood residents' perceptions of trust, helping behaviors, close ties, and how well they get along with their fellow neighbors may reduce violent victimization but would not likely decrease the occurrence of property crime. Residents who are personally connected to each other should be less willing to use violence to settle disputes. Second, these results suggest that residents' perception of law enforcement's ability to prevent crime and maintain order is important for reducing property crime but would likely have little impact on violent crime. Altering police activity in the neighborhood – for example, directed "hot spot" policing resulting in more arrests and increasing patrol routines for police visibility in areas with higher vandalism, burglary and/or larceny sites – may increase the probability of preventing and capturing neighborhood property offenders.

Our results clearly suggest that in order to reduce and prevent property crime victimization, community endeavors are needed that increase people's perceptions of the police as being able to do a good job at preventing crime and maintaining order in the neighborhood. However, our results also indicate some differential policy strategies are needed to reduce each type of property crime victimization. For example, reducing economic disadvantage may play a role in the reduction of larceny but do little to reduce burglary and vandalism victimization. Further, activities aimed at increasing informal control, where neighbors are willing to intervene to prevent crime and delinquency in the neighborhood, may reduce larceny and vandalism victimization (as well as violent crime victimization) but is unlikely to impact burglary victimization. Additionally, activities aimed at increasing residents' trust and ties to each other may help reduce larceny victimization but is unlikely to matter for the reduction of burglary and vandalism victimization.

Limitations

A significant limitation of this study concerns the measurement of the variables. As a secondary analysis of the PHDCN data, our study suffers the significant limitation of measuring residents' *perceptions* of social cohesion, informal control, police-citizen relations, and formal control, rather than the actual presence of these conditions in the neighborhood. For example formal control is generally considered to be a measure of police activity (e.g., patrols, arrests, etc.). We measure formal control as residents' perceptions of the ability of the police to prevent crime and maintain order in the neighborhood, rather than using official statistics of police activity. Future studies should include more direct measures of formal control.

Similarly, our indicator of informal control measures activity that *could* result in the use of informal social control, rather than actual measures of informal control. We measure informal control using survey items that refer to neighborhood residents' perceived willingness of themselves and others to utilize informal social control. While problematic, the extant literature has provided a precedent for use of such measures. For example, Sampson et al.'s (1997) concept of collective efficacy measures only the "willingness to intervene," not the action of the intervention itself. Future studies should include items specifically designed to tap the use of, rather than the perception of, informal control.

Further, our presentation of the results may be interpreted as assuming causal ordering of the variables. However, our use of cross-sectional data prohibits us from distinguishing the causal ordering of the relations variables and control variables. We cannot determine if social cohesion mediates the impact of neighborhood conditions on informal control and police-citizen relations mediates the impact of neighborhood conditions on formal control. These variables may have a reciprocal relationship, or the relationship may be in the opposite direction from the one we hypothesized. Future studies will benefit from a longitudinal design so that the causal ordering of the intervening variables may be assessed.

A final shortcoming that may limit the generalizability of our results is that the data come from the city of Chicago. The findings from our study need to be replicated using data from other cities and towns of varying size to ascertain whether the processes found in Chicago can be generalized. For example, do cities of more moderate size (e.g., 100,000 or 500,000 compared to Chicago's population of nearly 3 million) experience similar differential effects of social cohesion, informal control, police-citizen relations, and formal control on crime victimization? Does the racial and ethnic diversity of Chicago differentially impact the development and use of social cohesion, informal controls, police-citizen relations, and formal control? Do more homogenous cities (e.g., Des Moines, Iowa, Springfield, Missouri, or Fort Collins, Colorado) experience similar effects of negative neighborhood structural characteristics on the development of these relational and control variables, and do these effects differentially impact various types of victimization? These questions need to be addressed in future research using the systemic social disorganization model.

Endnotes

[1] We thank Robert Sampson for providing the ten census measures he and his colleagues used in the factor analysis in their original article (Sampson et al. 1997).

[2] This differs from the measure of concentrated disadvantage used by Sampson and his colleagues in that it excludes the percentage African American and percentage female-headed households from the composite measure. We use this measure because we believe it taps the elements that are most amenable to policy interventions to reduce and prevent crime. However, when we did use Sampson et al.'s measure, the results did not differ from those presented here.

[3] Unfortunately, the measure of interpersonal violence victimization in the PHDCN data set confounds violent crimes with an instrumental motive (i.e., mugging) with violent crimes that have an expressive motive (i.e., fight, sexual assault). As noted earlier, we expect differences in how perceptions of social cohesion, informal control, police-citizen relations, and formal control will impact crimes with instrumental motives versus crimes with expressive motives. Confounding of the two types of violence needs to be kept in mind when interpreting our results.

[4] In our earlier confirmatory factor analysis research we used Bayesian multiple imputation with non-numeric data (Arbuckle 2006).

[5] The hierarchical generalized linear two-level models were estimated using HLM 6.06 (Raudenbush et al. 2004).

[6] We conducted collinearity diagnostics to ascertain whether nonsignificant results in the models containing all social relations and control variables (i.e., Model 5 in Tables 2-5) were due to excessive multicollinearity. The results of our diagnostics show that our results are numerically stable with condition indexes well below the suggested 30 (Belsley, Kuh, and Welsch 1980; Belsley 1991:74). While several of the variance inflation factors (VIFs) in the full models exceeded the 2.5 criterion suggested by Allison (1999:141), inspection of the results in Tables 2-5 reveals that lack of statistical significance is due to the drop in effect size across models rather than inflated standard error estimates. As a final check, we re-ran Models 2-5 in Tables 2-5 with grand mean centering of the level-2 predictors. Without exception, the direction and statistical significance level of all effects are identical, and the magnitude of the effects is very similar. In sum, the results of our collinearity diagnostics demonstrate that we can have confidence in the veracity of our HGLM results presented in Tables 2-5. The results of these supplemental analyses are available upon request.

[7] The results of all unconditional means models are not shown.

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Appendix A. *Variable Names, Descriptions, Factor Loadings, Cronbach's α Coefficients, and Confirmatory Factor Measures of Fit*

Variable Names	Variable Descriptions
Neighborhood Structural Variables[1]:	
Economic Disadvantage	Factor score from a principal component analysis with % unemployed (.974)[2], % receiving public assistance (.984), and % living on incomes below the official poverty level (.963); α=.944.
Racial Heterogeneity	Index of diversity ($D = 1 - \sum p_i^2$) for the proportion white versus proportion not white.
Ethnic Heterogeneity	Factor score from a principal component analysis of the indexes of diversity for foreign born versus not foreign born (.938) and Latino versus not Latino (.938); α=.864.
Residential Stability	Factor score from a principal component analysis with % owner occupied households (.895) and % living in the same house as in 1985 (.895); α=.669.
Social Cohesion and Informal Control Variables:	
Social Cohesion	Factor score from the dimension of a confirmatory factor analysis with four items from the PHDCN (five-point Likert scales): This is a close-knit neighborhood (.734); People willing to help neighbors (.840); People don't get along (.578); People in neighborhood can be trusted (.712); α=.794.
Informal Control	Factor score from the dimension of a confirmatory factor analysis with four items from the PHDCN survey (five-point Likert items ranging from very unlikely to very likely): Do something kids skip school (.864); do something kids deface building (.819); Scold child for disrespect (.743); Break up a fight in front of house (.691); α=.841. Fit indices for the final confirmatory factor analysis model of social cohesion and informal control: χ^2=38.805; AGFI=.995; CFI=.999; RMSEA=.020; BIC=292.837; *r*=.666.
Police-Citizen Relations	Factor score from the dimension of a confirmatory factor analysis with two items from the PHDCN survey (five-point Likert scale from strongly agree to strongly disagree): Police are responsive to local issues (.818); Police do a good job with problems that concern people (.967); α=.869.
Formal Control	Factor scores from the dimension of a confirmatory factor analysis with two items from the PHDCN survey (five-point Likert scale from strongly agree to strongly disagree): Police not doing good job preventing crime (.779); Police not able to maintain order in streets (.645); α=.663. Fit indices for the final confirmatory factor analysis model of police-citizen relations and formal control: χ^2=5.858; AGFI=.997; CFI=1.00; RMSEA=.021; BIC=87.511; *r*=.595.

[1]All structural variables are derived from the 1990 U.S. Census.
[2]Factor loading from principal components analysis.

Appendix B. *Neighborhood-level Correlations*

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1. Economic disadvantage	1.000							
2. Residential stability	-.239**	1.000						
3. Ethnic heterogeneity	-.421**	-.347**	1.000					
4. Racial heterogeneity	-.022	-.388**	.241**	1.000				
5. Social cohesion	-.421**	.382**	-.083	-.135*	1.000			
6. Police-citizen relations	-.526**	.234**	.011	-.009	.584**	1.000		
7. Informal control	-.470**	.411**	-.075	-.131*	.839**	.636**	1.000	
8. Formal control	-.506**	.280**	-.028	-.112*	.545**	.855**	.587**	1.000

$^{*}p < .05$, $^{**}p < .01$ (two-tailed tests); n = 343.