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Neighborhood Context and Homicide Clearance: Estimating the Effects of Collective Efficacy

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Abstract

Only a handful of macro-level studies of homicide clearance exist, and the impact of community characteristics is mixed. In addition, community members are critical to clearances, but the willingness of residents to unite for the collective goal of aiding in investigations (via collective efficacy) remains to be tested. Combining data from the Chicago Police Department, Project on Human Development in Chicago Neighborhoods (PHDCN), and U.S. Census, we estimate the effect of collective efficacy on homicide clearances in Chicago neighborhoods, while taking into account neighborhood characteristics and case composition. Results indicate that economic disadvantage, residential stability, and victimization significantly decrease homicides clearances, while collective efficacy increases clearances.

Keywords

homicide clearance, collective efficacy, structural features, neighborhood effects, PHDCN

Introduction

Since the early 1990s, an average of 60% to 70% of all homicides are cleared by arrest or exceptional means nationally (Federal Bureau of Investigation [FBI], 2016). However, cities and the neighborhoods within them can vary widely from this national

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average. For example, larger cities tend to have lower clearance rates than smaller cities (FBI, 2016), and homicides that occur in certain neighborhoods remain harder to clear. In addition, homicide is the most cleared crime when compared with other offenses (FBI, 2016; Jarvis, Mancik, & Regoeczi, 2016; Litwin, 2004; Paré, Felson, & Ouimet, 2007), yet homicide clearance rates are still much lower today than they were a half-century ago. Low clearance rates not only prolong closure for the victims' friends and families but also have negative consequences on the broader community and for law enforcement. Lower clearance rates may heighten fear, contribute to distrust between neighborhood residents and law enforcement officers, and affect perceptions of police effectiveness (see, for example, Keel, Jarvis, & Muirhead, 2009; Ousey & Lee, 2010; Puckett & Lundman, 2003; Regoeczi, Kennedy, & Silverman, 2000). Low clearance rates may also reduce both general and specific deterrence mechanisms, inhibiting the effectiveness of the criminal justice system. Given these influential and far-reaching implications, an understanding of the factors that affect homicide clearances in urban environments is imperative.

However, research on macro-level constructs that account for the variation in homicide clearance rates across geographic areas is limited and empirical questions remain: How are community characteristics linked to homicide clearances and what role does neighborhood collective efficacy play in this process? This research utilizes data from the Project on Human Development in Chicago Neighborhoods (PHDCN) in a novel way—to test empirically the effect of collective efficacy on homicide clearances in Chicago neighborhoods, while also taking into account other neighborhood characteristics and homicide case composition.

Collective efficacy refers to social cohesion and trust among neighborhood residents combined with their willingness to intervene for the common good (Sampson, Raudenbush, & Earls, 1997). For reasons discussed below, collective efficacy should mobilize residents to aid in homicide investigations, thus increasing the likelihood that homicides will be cleared. Extant research finds that collective efficacy reduces a number of negative outcomes, including violent crime rates in neighborhoods (Sampson et al., 1997) and negative health outcomes, such as low birthweights and teen pregnancy (see Sampson, 2012, for a discussion), and increases the probability of arrest (Kirk & Matsuda, 2011). We extend the possible benefits of collective efficacy by examining whether it may also inform police clearance of homicides.

There is also mounting empirical evidence that legal factors, such as those related to the investigation and amount of physical and verbal evidence available, are among the most important in predicting whether a crime will be cleared or not. In fact, one of the most important tools available to investigators is the availability of and cooperation from witnesses and community members (see, for example, Carter & Carter, 2016; Greenwood, Chaiken, & Petersilia, 1977; Keel et al., 2009; Litwin, 2004; Puckett & Lundman, 2003; Regoeczi et al., 2000; Reiss, 1971; Riedel & Rinehart, 1996; Wellford & Cronin, 1999; Wolfgang, 1958), which may be enhanced in neighborhoods where collective efficacy is high.

A large body of research has established the importance of macrostructural predictors on rates of crime and violence. Not only are acts of crime and violence affected by

their broader ecological context, but their investigations are as well. As such, this research also considers the neighborhood context where these crimes occur (see also Petersen, 2017). In essence, this study is an examination of how neighborhoods matter for homicide clearance outcomes. Specifically, this research draws from social disorganization theory to examine the relationship between structural characteristics, collective efficacy, and homicide clearances. The objectives of this research are twofold. The first is to establish the links between neighborhood context, including neighborhood-level collective efficacy, and homicide clearances theoretically. The second is to offer an empirical test of homicide clearances at the neighborhood level.

Literature Review and Theoretical Frameworks

Within the homicide literature more broadly, research on factors affecting homicide clearance is relatively rare. In addition, most of the extant research on homicide clearance focused on victim- or incident-level predictors, and only a handful of studies considered the ecological context where these crimes occur and how this may influence homicide case outcomes. For instance, scholars examined neighborhood effects on homicide clearances in Chicago (Litwin, 2004; Litwin & Xu, 2007; Xu, 2008), Cleveland (Regoeczi & Jarvis, 2013), Columbus (Lundman & Myers, 2012; Puckett & Lundman, 2003), and Los Angeles (Lee, 2005; Petersen, 2017), and others focused on factors affecting homicide clearance rates for large U.S. cities (Borg & Parker, 2001; Ousey & Lee, 2010). In addition, Ganley (2016) compared the factors affecting homicide clearance rates in small towns versus large cities in Colorado.

Social Disorganization and Structural Features

Research on community variation in homicide clearance rates draws largely from social disorganization theory to explain the role of ecological characteristics on homicide case outcomes. Social disorganization theory posits that neighborhoods characterized by structural barriers, such as poverty and residential instability, will experience a breakdown in informal social control, thereby leading to increased crime rates (Sampson & Groves, 1989; Shaw & McKay, 1942; Shaw, Zorbaugh, McKay, & Cottrell, 1929). Scholars have since articulated the theoretical linkages between these structural features and various criminal justice outcomes, including clearance and prosecution (see, for example, Regoeczi & Jarvis, 2013).

The empirical research analyzing the structural determinants of homicide clearance produces mixed findings, however. Results regarding the impact of economic indicators on homicide clearances are inconsistent across studies. For example, Petersen (2017) found that concentrated disadvantage was positively associated with homicide clearance in Los Angeles in the 1990s, and Ousey and Lee (2010) found that within-city changes in levels of resource deprivation was positively related to changes in homicide clearance rates over time. However, in their study of homicide clearances in Chicago for three time periods, Litwin and Xu (2007) found economic disadvantage was only significant in the last time period (i.e., 1986-1995), with community areas

with higher levels of economic disadvantage experiencing lower likelihoods of homicide clearance during this time period. Furthermore, several studies have found no relationship between several different indicators of economic conditions and homicide clearance (Borg & Parker, 2001; Hawk, 2015; Litwin, 2004; Puckett & Lundman, 2003; Regoeczi & Jarvis, 2013; Xu, 2008).

Most macro-level studies of homicide clearance also include a measure of racial composition. Although racial composition is often included in an index of economic disadvantage, some scholars have analyzed the impact of racial composition separately, with mixed results as well. For example, Puckett and Lundman (2003) and Lundman and Myers (2012) found that predominately African American neighborhoods (identified as those census tracts with more than 1 standard deviation above the mean percent Black) were associated with declines in clearance. However (Xu, 2008) found that the percent of African Americans in the population was positively associated with homicide clearance rates using two different longitudinal methods, whereas Litwin and Xu (2007) found no effect across the three time periods examined in their study. Furthermore, in his multilevel analysis of incident, neighborhood, and agency-level factors affecting homicide clearance in Los Angeles County, Petersen (2017) found that racial composition had significant negative effects on clearance above and beyond influences of victim race.

Macro-level studies of homicide clearance also tend to find mixed results for indicators of residential (in)stability. For example, Borg and Parker (2001) found that residential mobility was negatively associated with homicide clearance rates in large U.S. cities; however, others found no effect (Ousey & Lee, 2010; Regoeczi & Jarvis, 2013). Interestingly, although they did not find a main effect, Regoeczi and Jarvis (2013) found that residential instability moderated the effect of White victims on homicide clearance outcomes.

Finally, very few studies considered how the relative size of the immigrant population may affect homicide clearance outcomes. However, several studies found that homicides with Latino victims were less likely to be cleared than homicides with either Black or White victims (e.g., Alderden & Lavery, 2007; Litwin, 2004; Litwin & Xu, 2007; Regoeczi et al., 2000; Xu, 2008), and they attributed this finding to more negative relationships between Latinos and police and potential language barriers (Alderden & Lavery, 2007). Litwin and Xu (2007) also found that the percentage of the population that was Spanish-speaking significantly decreased the odds of clearance in their final time period (i.e., 1986-1995). The one study that did consider the relative size of the immigrant population found that changes in immigration had a negative association with within-city changes in homicide clearance rates over time (Ousey & Lee, 2010).

Collective Efficacy and Community Engagement

Despite the mixed findings on the role of ecological context on homicide clearances, one of the most consistent findings in the crime clearance literature is the importance of community members for successful clearance outcomes. Without question, research

shows that community members play a crucial role in homicide clearances (see, for example, Greenwood et al., 1977; Keel et al., 2009; Litwin, 2004; Mouzos & Muller, 2001; Puckett & Lundman, 2003; Regoeczi et al., 2000; Reiss, 1971; Riedel & Rinehart, 1996; Schroeder & White, 2009; Wellford & Cronin, 1999; Wolfgang, 1958). For example, in an analysis of comments made by police supervisors, Keel and his colleagues (2009) concluded that "public cooperation [is] a key element in successful homicide investigations" (p. 65). This cooperation from witnesses and community members may be even more critical for homicides in which victims cannot aid in the investigation. In addition, despite technological advancements and increased emphasis and attention to the role of DNA and other forensic evidence as contributing to successful clearance outcomes, recent research finds that eyewitness testimony and cooperation from community members is critical to clearing homicides, even after controlling for a host of forensic factors (e.g., Braga & Dusseault, 2016; Davis, Jensen, Burgette, & Burnett, 2014; McEwen & Regoeczi, 2015; Schroeder & White, 2009). Community members' engagement may enhance the likelihood of case clearances through factors such as increased witness cooperation and willingness to come forward with information (e.g., Wellford & Cronin, 1999), increased willingness of community members to lobby for additional police resources (Borg & Parker, 2001), or community members pushing police for a more thorough investigation (Paré et al., 2007).

More recently, extensions of social disorganization theory further clarified the relationship between ecological structural features and neighborhood variation in crime rates, with the theoretical construct of collective efficacy. This construct refers to the combination of social cohesion and trust between neighbors and their willingness to intervene for a collective goal, that is, engage in informal social control (Sampson et al., 1997). Research found that neighborhoods vary in their ability to produce collective efficacy, and that concentrated disadvantage and immigrant concentration decrease neighborhood collective efficacy, while residential stability increases the level of collective efficacy (e.g., Sampson et al., 1997). Considering the inconsistent role of structural features and the importance of community members for successful clearance outcomes, collective efficacy may aid in our understanding of neighborhood variation in homicide clearance rates. Although originally offered to explain the link between structural features and crime rates, there are theoretical reasons to believe collective efficacy may affect homicide clearances as well.

A key component of collective efficacy is social cohesion, which refers to the ability of community members to realize collective and prosocial goals. Sampson and his colleagues (1997) gave the example of residents working together to achieve the collective goal of living in a crime free area. This desire to live in a safer environment should not only help mobilize residents to engage in actions to thwart crime in their communities but also to seek justice for those who engage in crime and remove potentially dangerous offenders from their streets. Until the homicide is cleared, the offender may remain in or travel within the neighborhood, potentially causing more harm. As a result, residents in neighborhoods with higher levels of collective efficacy may be more likely to aid in investigations or lobby for increased police resources and time to solve the homicide due to their mutual desire to live in a safe environment.

Another key element of collective efficacy is trust between neighborhood residents. During interviews and observations, researchers have found that fear of retaliation for cooperating with police is a major obstacle police must overcome in homicide investigations (Maguire, King, Johnson, & Katz, 2010; Regoeczi & Jarvis, 2013; Westmarland, 2013). Even if residents want to cooperate in a police investigation, fear of retaliation may hinder their involvement. For example, Anderson (1999) claimed that people often conceal having seen a crime to avoid being targeted for snitching (see also Jackall, 2005, discussion of community members being "scared stiff" to get involved during homicide investigations due to possible retaliation, p. 168). In short, community members should be less likely to engage in collective actions, such as aiding in a homicide investigation, in neighborhoods with low levels of collective efficacy, where residents may distrust or fear one another. However, in areas with higher levels of collective efficacy and increased trust between residents, witnesses should be less fearful of retaliation and more willing to cooperate (Regoeczi & Jarvis, 2013).

Collective efficacy also captures community-level informal social controls. Informal social control relates to the community's willingness to work together collectively to solve problems and achieve common goals for the well-being of the community (Sampson et al., 1997). For example, feelings of empowerment among residents to address local crime problems may contribute to their increased willingness to lobby for more police resources (Borg & Parker, 2001), push police for a more thorough investigation (Paré et al., 2007), or establish a neighborhood watch group. With increased supervision, the likelihood that someone will have information that could be useful for clearing a case increases (Litwin, 2004; Regoeczi & Jarvis, 2013). In addition, increased pressure by community members may increase resources and investigative effort by police, thereby increasing the likelihood of a homicide being cleared.

While the effects of collective efficacy on crime clearance have yet to be tested empirically, in a recent study, Regoeczi and Jarvis (2013) found that third parties significantly increased the odds that homicides are cleared, but this effect was reduced in disadvantaged neighborhoods. That is, neighborhood disadvantage moderated the relationship between third parties and homicide clearances. They speculated this may be because there is lower collective efficacy in disadvantaged neighborhoods, reducing the likelihood that witnesses would cooperate with police to clear the case.

For each of the reasons discussed above, collective efficacy should increase neighborhood homicide clearance rates. As such, we hypothesize that homicide clearances will be higher in neighborhoods with higher levels of collective efficacy. We also consider the possibility that collective efficacy mediates the impact of structural features on homicide clearances, as it has been found to do with crime rates (e.g., Sampson et al., 1997).

Method

Data and Sample

This study focuses on neighborhood variation in homicide clearance in Chicago, Illinois. Chicago was chosen because of the accessibility of data, high violent crime

rate, and diversity of neighborhoods. In addition, analyzing clearances at the neighborhood level provides the best test of collective efficacy consistent with Sampson et al.'s (1997) original conceptualization, and research shows that neighborhood context is an important consideration of police behavior (Smith, 1986; Terrill & Reisig, 2003). Furthermore, in her doctoral dissertation, Hawk (2015) argued that comparing clearance results across jurisdictions may be problematic because "it is likely that the demographics of smaller geographic units, such as census tracts or neighborhoods, more strongly affect the chances a case will be solved" (p. 17) and that aggregating information to the city level (e.g., racial composition) misses important dynamics at these smaller units of analysis, which may affect clearance.

Sampson and his colleagues (1997) combined approximately two to three contiguous census tracts to form 343 meaningful "neighborhood clusters," which they argue are more meaningful to capture neighborhood dynamics than smaller census tracts, or larger community areas. Not only were these census tracts in close geographic proximity to one another, but they were characterized by similar racial/ethnic composition, socioeconomic status, housing density, and family structure. They were also based on residents' perceptions of their neighborhoods. Therefore, data from the different sources described below were gathered at the census tract level, matched on census tract identifiers, and then aggregated to the neighborhood cluster (NC)[1] level for statistical analyses.

A multisource data collection approach was used, merging data from several different secondary sources. First, the Chicago Police Department provided homicide and homicide clearance data for the years 1996 to 2000. Homicides were matched with the 1990 census tracts in which they occurred. Second, measures used to create the collective efficacy scale, as well as control measures for neighborhood victimization and legal cynicism, came from the "Project on Human Development in Chicago Neighborhoods: Community Survey, 1994-1995" dataset (PHDCN: CS) available through the Inter-university Consortium for Political and Social Research (ICPSR) at the University of Michigan. Third, neighborhood-level measures of social, economic, and demographic conditions came from the 1990 U.S. Census (Minnesota Population Center, 2011).[2] Although these data are from the 1990s, they are ideal for the current study by providing the measures necessary to examine the relationship between collective efficacy and homicide clearances, which has yet to be tested empirically.

Dependent Variable

The dependent variable used in this analysis is the neighborhood count of homicides cleared by either arrest or exceptional means (i.e., homicide clearances) between 1996 and 2000.[3] Data from the Chicago Police Department do not differentiate between homicides that were cleared by arrest versus homicides cleared by exceptional means. The 5-year sum was used due to the small number of homicides that occur each year and to compensate for any year-to-year fluctuations in the data, consistent with previous macro-level studies of rare events (e.g., Borg & Parker, 2001; Krivo & Peterson, 1996; Morenoff, Sampson, & Raudenbush, 2001). The models also include an offset variable for the total count of homicides known to police, which represents the total

number of opportunities that an event (e.g., clearance) can occur. Therefore, the homicide count was taken into account when estimating the total count of cleared homicides, essentially converting the dependent variable to a ratio of homicides cleared to homicides known to police (Osgood, 2000).

This study only includes those neighborhoods where at least one homicide occurred between 1996 and 2000 because a homicide is necessary for it to be potentially cleared (see Litwin, 2004, for a similar approach). This resulted in an initial sample of 321 neighborhoods.

Independent Variables

Structural features. Consistent with social disorganization theory and previous tests of collective efficacy, this study used the following 10 measures gathered from the 1990 U.S. Census Bureau: poverty (percent of families living below the poverty line), public assistance (percent of households receiving public assistance), racial composition (percent African American), family disruption (percent of female-headed families with children), unemployment (percent of the civilian labor force that is unemployed), homeownership (percent of owner-occupied housing units), residential stability (percent of residents who lived in the same house 5 years prior, that is, in 1985), and several measures indicative of immigration (percent Hispanic residents, percent foreign-born, and percent Spanish-speaking).

Collective efficacy. To test collective efficacy most accurately, this study follows the strategy set out by Sampson et al. (1997) in creating the collective efficacy measure. Collective efficacy was measured by averaging neighborhood-level informal social control and social cohesion/trust scales constructed from the PHDCN. Specifically, *informal social control* was measured by averaging neighborhood respondents' answers to five questions asking about the likelihood that neighbors would intervene if

> (i) children were skipping school and hanging out on the street corner, (ii) children were spray-painting graffiti on a local building, (iii) children were showing disrespect to an adult, (iv) a fight broke out in front of their house, and (v) the fire station closest to their home was threatened with budget cuts. (Sampson et al., 1997, pp. 919-920)

Responses for each question ranged from 1 (*very unlikely*) to 5 (*very likely*). In the combined informal social control scale, higher scores represent increased willingness to intervene, and thus more informal social control. In addition, *social cohesion and trust* was measured by averaging respondents' answers on the extent to which they agree with the following five statements:

> "People around here are willing to help their neighbors," "this is a close-knit neighborhood," "people in this neighborhood can be trusted," "people in this neighborhood generally don't get along with each other," and "people in this neighborhood do not share similar values" (the last two statements were reverse coded). (Sampson et al., 1997, p. 920)

Responses to these questions ranged from 1 (*strongly disagree*) to 5 (*strongly agree*). Therefore, in the combined social cohesion and trust measure, higher numbers represent more social cohesion/trust. The informal social control and social cohesion/trust measures had high reliability across neighborhoods ($r = .88$).[4] Therefore, these measures were combined into a single construct, *collective efficacy*, averaging the two scales. The final scale ranged from 1 to 5, with higher numbers indicating more collective efficacy.

Control Variables

This study offers a number of control measures which may be important predictors of homicide clearance. Specifically, models control for the composition of homicide incidents across neighborhoods. The homicide clearance literature has established the importance of various case characteristics for homicide clearance outcomes. For example, research finds that homicides committed with a firearm are more difficult to clear (Jarvis et al., 2016; Litwin, 2004; Litwin & Xu, 2007; Mouzos & Muller, 2001; Regoeczi et al., 2000; Rydberg & Pizarro, 2014), as are those committed by a stranger (Alderden & Lavery, 2007; Jarvis et al., 2016; Jiao, 2007; Lee, 2005; Xu, 2008). It is possible that these harder to clear cases are concentrated in certain neighborhoods. Therefore, neighborhood variation in homicide clearance rates could be due to the make-up of homicides that occur in those neighborhoods, rather than to ecological characteristics or collective efficacy. To control for potential differences in case composition of homicide incidents across neighborhoods, this study also includes the percent of homicides committed with a firearm, involving a stranger, occurring in a residence, with a male victim, and with a White victim. Although results for victim demographics, such as race and gender, have been inconsistent in the literature, we include measures of the percent of homicides with a male victim and a White victim because measures of victim race and gender are often included in clearance studies. To ensure that clearances were not double counted for incidents involving multiple victims, calculations were done for homicide incidents and based off of data for the first victim only. These variables were computed by summing the total number of homicides in each NC over the 5-year span that were *known to police* to have a particular characteristic (e.g., the total number of homicides where it was known to police that the offender was a stranger) divided by the total number of homicides that occurred in that NC over the 5 years, multiplied by 100.

This study also controls for recent neighborhood victimization as a proxy for neighborhood crime levels. The models include a measure of reported victimization in the past 6 months drawn from the PHDCN. We argue that one possible reason community members may not cooperate with police is because they fear retaliation for doing so; therefore, we include a measure of victimization in the past 6 months as a proxy for neighborhood-level crime. This also allows us to test an alternative explanation for the impact of collective efficacy on homicide clearance rates, specifically, that collective efficacy reduces the amount of crime in the neighborhood as found by previous research (e.g., Sampson et al., 1997), thus decreasing resident fear for cooperating

with police. Neighborhood crime levels may also affect police workload and thus clearances. Although we incorporate this measure into the multivariate models, readers should interpret results of this measure with caution because a main limitation of the self-report measure is that respondents who are unwilling to self-report their victimization experiences may also be unwilling to provide information to police. Therefore, the error for the two measures may be correlated. While it would be preferable to include the official non-lethal violent crime rate, the researchers did not have access to these data.

In addition, this research controls for neighborhood-level legal cynicism. Legal cynicism refers to a cultural orientation in which community members view the law and agents of its enforcement as illegitimate (Kirk & Papachristos, 2011). Therefore, legal cynicism and lack of trust in police may hinder relationships between neighborhood residents and law enforcement in their communities and reduce community members' willingness to work with police, making clearing homicides more difficult (Petersen, 2017). Research also found that strong and trustworthy relationships between police and community members are crucial for agencies' success (e.g., Carter & Carter, 2016). Recognizing the potential countervailing impact of legal cynicism on resident cooperation with police and thus homicide clearances, this study controls for legal cynicism to isolate the effects of collective efficacy, net of legal cynicism. Legal cynicism was measured by averaging respondents' answers from the PHDCN: CS to the following statements:

> (1) the police are not doing a good job in preventing crime in this neighborhood, (2) the police are not able to maintain order on the streets and sidewalks in the neighborhood, and (3) laws are made to be broken. (Kirk & Matsuda, 2011, p. 454)

Responses ranged from 1 (*strongly disagree*) to 5 (*strongly agree*). The combined legal cynicism scale ranged from 1 to 5, with higher numbers indicating more legal cynicism.

Finally, consistent with other aggregate studies of criminal justice outcomes, statistical models also controlled for the area population by including the natural log of the total number of residents (in thousands) living in each neighborhood cluster in 1990 (see, for example, Borg & Parker, 2001). This is also theoretically meaningful as both Wirth (1938) and Wolfgang (1958) discussed the potential for more anonymous relationships in more heavily populated areas. With this greater anonymity, witnesses and police may be less likely to identify suspects (Felson, 1998), and homicides may be less likely to be cleared.

Methodological Issues

A preliminary exploration of the variables revealed problems with multicollinearity between the covariates. Consequently, factor analysis was used to reduce the regressor space shared between variables (Land, McCall, & Cohen, 1990). Exploratory factor analysis of the ten 1990 census variables resulted in the creation of three unique factors: an economic disadvantage index, an immigrant concentration index, and a residential

Table 1. Principal Axis Factor Analysis of Chicago Neighborhood 1990 Census Variables After Oblimin Oblique Rotation (N = 321).

Variable	Factor loading	Variance explained
Economic disadvantage		48.68%
Households on public assistance	.9743	
Families below poverty line	.9475	
Unemployment	.9550	
Female-headed households with children	.9526	
Black	.6665	
Immigrant concentration		30.07%
Spanish-speaking	.9900	
Hispanic	.9855	
Foreign-born	.5220	
Residential stability		16.88%
Same house in 1985	.7991	
Owner-occupied housing units	.7299	

Note. Eigenvalues > 1.0.

stability index. These indices and their components are similar to previous tests of collective efficacy (e.g., Kirk & Matsuda, 2011; Morenoff et al., 2001; Sampson et al., 1997). The *economic disadvantage* index includes percent of families living below the poverty line, percent of households receiving public assistance, percent of female-headed families with children, percent of residents unemployed in the civilian labor force, and percent African American. The *immigrant concentration* index includes percent of foreign-born residents who entered the U.S. in the past 10 years, percent Spanish-speaking residents, and percent Hispanic residents. The third index, *residential stability*, includes the percent of residents who lived in their same house 5 years prior (i.e., in 1985) and percent of homeowners. Similar to Land et al. (1990) and other macro-level studies, all indices were computed as composite measures by summing each component weighted by its factor loading, for example, economic disadvantage = ([% households on public assistance × .9743] + [% families below poverty line × .9475] + [% unemployed × .9550] + [% female-headed households with children × .9526] + [% Black × .6665]). All of the resulting factors had Eigenvalues greater than 1 and factor loadings greater than 0.60 (with the exception of percent foreign-born which was .52). Results from the factor analysis, including the components, their factor loadings, and the percentage of variance explained by each factor are displayed in Table 1. Collinearity diagnostics for these newly created factors indicated no problems (Kennedy, 1998). Variance Inflation Factor (VIF) results are presented at the bottom of Table 2.

Population size was log transformed to better fit the distribution and reduce skewness in the measure. A generalized linear model with the Negative Binomial family and link log specified was estimated, to assess problems with hetereoskedasticity and identify potential influential outliers. This analysis resulted in the identification of one potential outlier with a Cook's distance score greater than 0.30, whereas the mean

Table 2. Descriptive Statistics of Dependent and Predictor Variables Included in Final Models (n = 319).

Variables and index components	*M*	*SD*	Median	Minimum	Maximum
Homicide clearance rate[a]	67.72	23.61	66.67	0.00	100.00
Homicide clearance counts	7.13	6.68	5.00	0.00	44.00
Homicide counts	11.05	9.94	8.00	1.00	62.00
Homicide rate (per 1,000)	1.47	1.22	1.15	0.067	6.62
Economic disadvantage index	94.50	71.81	74.94	6.53	331.49
% families below poverty line	21.51	17.32	15.91	0.231	88.18
% households on public assistance	18.43	15.06	13.35	1.11	77.26
% unemployed	14.47	9.34	12.07	1.90	52.01
% female-headed with children	13.87	11.34	10.18	0.482	67.38
% Black	43.72	43.85	21.34	0.00	99.61
Immigrant concentration index	41.90	50.24	18.29	0.647	188.31
% foreign-born	7.53	8.71	4.04	0.00	46.60
% Spanish-speaking	17.22	21.33	5.69	0.00	80.18
% Hispanic	21.17	26.66	8.16	0.120	95.83
Residential stability index	72.87	23.68	69.05	26.36	132.57
% owner-occupied housing units	38.33	22.69	33.35	0.532	92.50
% same house in 1985	56.18	12.32	57.73	26.73	82.42
Population size	8,047	2,879	7,754	2,279	25,231
Population size per 1,000 (log)	2.02	0.371	2.05	.824	3.23
Victimization	0.423	0.232	0.396	0.00	1.21
Legal cynicism	2.49	0.308	2.53	1.55	3.06
Collective efficacy[b]	3.41	0.328	3.40	2.55	4.33
% White victim	45.54	43.22	33.33	0.00	100.0
% male victim	79.59	22.81	85.71	0.00	100.0
% stranger	24.52	24.06	20.00	0.00	100.0
% firearm	67.61	27.25	75.00	0.00	100.0
% residence	23.45	25.61	16.67	0.00	100.0

Note. Multicollinearity is not an issue; highest Variance Inflation Factor = 4.28; mean = 2.31 in Model 3.
[a]Calculated using 5 years of data (1996-2000).
[b]α = .8824.

score across all neighborhoods was .011 and the median was .003.[5] Removing this NC resulted in a final sample of 320 neighborhoods, which was further reduced to 319 NCs in the final analysis due to missing data. In addition, regression models were estimated with the robust standard errors option to compensate for any problems with heteroskedasticity.

Analytic Strategy

Due to the rare nature of homicide clearances and a highly positively skewed distribution of the homicide clearance count (and highly negatively skewed distribution of the

percentage of homicides cleared), a Poisson-based estimation approach was used. We choose to use a count model as opposed to an ordinary least squares (OLS) model with the percent of homicides cleared as the dependent variable due to the skewed nature of the dependent variable and because transformations (i.e., natural log and square root) did not induce normality.

Poisson models assume the mean and variance of the dependent variable are equal (i.e., equidispersed). However, the dependent variable in these analyses, the homicide clearance count, is overdispersed. Therefore, analyses were conducted using the negative binomial variant of the Poisson model. The negative binomial model is more appropriate because it includes an error term that accounts for this overdispersion. Significant results for several statistical tests (i.e., Likelihood Ratio test, Deviance Goodness of Fit test, and Pearson Goodness of Fit test) also indicated that the negative binomial was a better option than the Poisson model. As discussed above, the negative binomial count model included the total number of homicides known to police as an offset variable, representing the total number of opportunities that clearance can occur. Including the offset variable introduced the total number of homicides known to police as a variable in the model, but constrained the slope to one. Therefore, the total number of homicides that occurred is taken into account when estimating the total number of homicides that were cleared.

Results

Descriptive Statistics

Table 2 provides detailed descriptive statistics for the 319 neighborhoods included in the full models. The average percentage of homicides cleared across Chicago neighborhoods is 67.72%, which is slightly higher than the national 5 year average for 1996 to 2000 for all cities (FBI, 1997, 1998, 1999, 2000, 2001). Table 2 is provided largely as a resource to show that the social and economic composition of neighborhoods varies substantially. Furthermore, neighborhoods score moderately high on collective efficacy, with an average value of 3.41, although neighborhood levels of collective efficacy range from 2.55 to 4.33.

Regression Results

Table 3 presents results from a series of negative binomial regression models. Both exponentiated coefficients (i.e., Incidence Rate Ratios or "IRR") and exponentiated coefficients with standardized independent variables are reported. An IRR of 1.0 indicates no effect of the independent variable on the homicide clearance count. An IRR greater than 1.0 indicates that the independent variable has a positive effect, and an IRR less than 1.0 indicates that the independent variable has a negative effect. IRRs can also be interpreted in terms of a percent change in the expected homicide clearance count with a one-unit increase in the independent variable (or a 1 standard deviation increase for the standardized measures).

Table 3. Negative Binomial Regression Predicting Homicide Clearance Counts, Offset by Total Homicides, Exponentiated Coefficients and (Robust Standard Errors) Reported.

	Model 1		Model 2		Model 3	
Variable	e^*b*	e^*b*Std*X*	e^*b*	e^*b*Std*X*	e^*b*	e^*b*Std*X*
Economic disadvantage	0.9570*** (.007)	0.0427	0.9601*** (.007)	0.0537	0.9699*** (.007)	0.1194
Immigrant concentration	0.9918 (.005)	0.6615	0.9918 (.005)	0.6620	0.9886 (.007)	0.5310
Residential stability	0.9694*** (.009)	0.4786	0.9570*** (.009)	0.3534	0.9644* (.014)	0.4593
Population size (log)	0.0188*** (.011)	0.2290	0.0179*** (.010)	0.2246	0.0238*** (.017)	0.2409
Victimization	0.0788** (.075)	0.5537	0.1134* (.102)	0.6026	0.0251*** (.028)	0.4175
Legal cynicism	0.5026 (.443)	0.8092	1.348 (1.41)	1.096	4.532 (5.40)	1.446
Collective efficacy	—	—	11.44** (10.37)	2.222	14.84** (14.09)	2.134
% White victim	1.009 (.007)	1.463	1.011 (.007)	1.597	1.042*** (.012)	5.062
% male victim	1.000 (.005)	1.003	0.9961 (.005)	0.9143	0.9802 (.019)	0.7573
% stranger	0.9934 (.005)	0.8529	0.9939 (.005)	0.8637	0.9976 (.014)	0.9636
% firearm	1.003 (.006)	1.072	1.003 (.006)	1.089	1.034* (.015)	1.890
% residence	1.006 (.005)	1.163	1.006 (.006)	1.178	1.042 (.022)	2.039
n	319		319		236	
Log pseudolikelihood	−1,440.96		−1,437.31		−1,209.84	
BIC	2,956.86		2,955.34		2,496.18	
Pseudo R^2	.0447		.0471		.0336	

Note. BIC = Bayesian information criterion.
*$p < .05$. **$p < .01$. ***$p < .001$.

IRRs from the baseline negative binomial regression model, which does not include collective efficacy, are presented in Model 1. Specifically, Model 1 shows the effects of structural characteristics, neighborhood victimization, legal cynicism, area population, and case characteristics on homicide clearance counts and provides a baseline model with which to compare the subsequent model once collective efficacy is added. Results indicate that economic disadvantage, residential stability, population size, and neighborhood victimization are significantly associated with a decrease in the

homicide clearance count in the baseline model. Specifically, a one unit increase in the economic disadvantage index is associated with a 4.3% decrease in the expected homicide clearance count.[6] Furthermore, a one unit increase in the residential stability index is associated with a 3.1% decrease and in the expected homicide clearance count. Surprisingly, results also indicate that immigrant concentration, legal cynicism, and each of the case characteristics are unrelated to homicide clearances.

Results displayed in Model 2 of Table 3 show results for the full model. That is, Model 2 shows the effects once collective efficacy is added to the model. Doing so provides a better fit to the data than Model 1, as indicated by the log likelihood closer to zero and the lower Bayesian information criterion (BIC).[7] Furthermore, a likelihood-ratio test comparing the nested models indicated significant differences between the two models, with Model 2 providing a significantly better fit to the data ($\chi^2 = 6.11$; $p = .013$). Collective efficacy has a strong and significant positive effect on the homicide clearance count, as hypothesized. Specifically, the homicide clearance count is expected to increase by a factor of 2.2 with a 1 standard deviation increase in collective efficacy.

Economic disadvantage, residential stability, and population size all remain significant with relatively small changes in their IRRs, even after collective efficacy is added to the model, indicating their independent effects above and beyond their influence on collective efficacy. While it appears that a majority of the effect of the structural features on homicide clearances is direct, the coefficient for economic disadvantage is reduced somewhat once collective efficacy is added to the model, indicating collective efficacy may be mediating the effect, but only very slightly. A one unit increase in the economic disadvantage index is now associated with a 4.0% reduction in the homicide clearance count (as compared with a 4.3% reduction in Model 1). The addition of collective efficacy to the model, however, actually increases the effect of residential stability, indicating a possible suppression effect.

The effect of neighborhood victimization is still significant; however, it dropped in both magnitude and significance (i.e., from an IRR of .0788 to an IRR of .1134) indicating a potential mediating effect of collective efficacy on the relationship between victimization and homicide clearance. Once again, immigrant concentration, legal cynicism, and the homicide case characteristics are not significant.

Supplemental Analyses

Neighborhoods in our sample exhibited a great deal of variability in their levels of lethal violence from 1996 to 2000 (i.e., ranging from only one homicide to 62 homicides). As such, we explored the possibility that results are biased by the inclusion of low homicide neighborhoods in our full analysis. Model 3 presents results from a supplemental analysis in which neighborhoods with very low homicide counts were removed to ensure that these low homicide neighborhoods were not driving results. Neighborhoods that experienced three or fewer homicides over the 1996 to 2000 time frame (i.e., those in the lower quartile) were excluded from the supplemental analysis. This subsample analysis revealed a number of interesting findings. First, economic

disadvantage, residential stability, population size, victimization, and collective efficacy, which were significant in previous models, all remained significant and in the same direction as Models 1 and 2. However, some of the homicide case compositional variables reached significance. Specifically, results indicate that NCs with greater percentages of homicides involving White victims and NCs with greater percentages of firearm-related homicides experience higher homicide clearances.

As a second sensitivity analysis, the full model (i.e., Model 2) was estimated using jackknifed standard errors. Results are not presented in Table 3, as this only affects the standard errors, and the coefficients remain the same. In essence, this procedure performs multiple iterations of the analysis dropping and replacing one NC at a time, performing 320 replications of the analysis in calculating the standard errors. Using the jackknife procedures, results did not change for economic deprivation, residential stability, or population size. Both victimization and collective efficacy, however, dropped to marginally significant. Immigrant concentration, legal cynicism, and the homicide case compositional variables remained insignificant.

Finally, in an effort to further understand the link between collective efficacy and homicide clearances, and drawing on more recent debates questioning whether social cohesion and trust and informal social control may be two distinct constructs (see, for example, Hipp & Wo, 2015), the researchers also ran models testing the effects of the two components of collective efficacy (i.e., social cohesion and informal social control) separately. Results reveal that social cohesion is significantly and positively associated with homicide clearances (e^b = 25.09; e^bStd$X$ = 2.74; p = .004), whereas informal social control does not have an effect. This is consistent with earlier empirical work that has separated the constructs and finds that high levels of social cohesion significantly affects the outcome of interest, but that it does not necessarily translate into collective action, with informal social control being insignificant or weakened when the two are separated (e.g., Armstrong, Katz, & Schnebly, 2015; Horne, 2004; Reisig & Cancino, 2004; Williams & Guerra, 2011). Results for all other variables in the model remained substantively similar to those presented in Model 2.

Discussion

Results from these analyses provide support for the argument that neighborhood context matters for the successful clearance of homicides. Sampson (2008) argued that collective efficacy is situational, that is, it "exists relative to specific tasks." It appears that the neighborhood mechanism of collective efficacy "exists" in relation to police clearance of homicides. Specifically, as hypothesized, collective efficacy was positively associated with homicide clearances, even after taking into account other neighborhood features and the composition of homicides in the neighborhood.

Results from these analyses also suggest that structural features of neighborhoods are important independent predictors of homicide clearances, even after controlling for a key mechanism thought to affect community participation, collective efficacy. Previous studies found that collective efficacy mediates the effects of structural features on neighborhood crime rates (e.g., Sampson et al., 1997), and we believed that

the primary impact of structural features on homicide clearances would be through collective efficacy. That is, that collective efficacy would mediate the relationship between structural features and homicide clearances, as found in previous studies of crime rates. However, this is not what our results show. It is possible that collective efficacy does not mediate the effect of structural features because of the different outcome examined (i.e., a criminal justice outcome as opposed to crime rates). Instead, results indicate that structural features exert strong direct effects on homicide clearance, independent of their effects through collective efficacy. We offer a few possibilities for the finding of a lack of mediation.

First, results reveal that economic disadvantage significantly decreases the homicide clearance count above and beyond its influence through collective efficacy. One possibility is that police may use information on the neighborhood's racial and socioeconomic make-up when drawing inferences about the victim's culpability, potentially affecting clearance processes (see also Petersen, 2017). Furthermore, qualitative research conducted in the Caribbean found a self-fulfilling prophecy between witness cooperation and police investigative effort. That is, police assumed that cooperation from community members had declined which ultimately contributed to police cutting back on investigative efforts, such as canvasing the area and less effort to reach out to community members (Maguire et al., 2010).

Results indicate that residential stability is associated with a decrease in homicide clearances. This is somewhat surprising as previous research on the effects of residential instability on homicide clearances has either found no effect (Ousey & Lee, 2010; Regoeczi & Jarvis, 2013) or a negative (positive) effect of instability (stability) on homicide clearances (Borg & Parker, 2001; Litwin, 2004; Xu, 2008). Furthermore, the negative effects of residential stability actually *increased* once collective efficacy was added to the model. One admittedly speculative reason for the negative relationship found here is that in more stable neighborhoods, residents may be more aware of informal rules not to talk to or cooperate with police, thus contributing to a negative association between residential stability and homicide clearances. This may be particularly true if residents in these stable neighborhoods do not trust their neighbors (i.e., social cohesion is low), particularly in light of the finding that social cohesion/trust appears to be the driving force in the positive association between collective efficacy and homicide clearances (see also the discussion of negotiated coexistence by Browning, 2009; Browning, Feinberg, & Dietz, 2004). That is, stability without trust/cohesion may actually hinder clearances if norms discourage cooperation with police. Regardless of the reasons, it is important to emphasize that these findings are consistent across models, with relatively stable effect sizes, even after controlling for collective efficacy, indicating important direct effects of structural features on homicide clearances (or indirect through mechanisms not captured in this study). The robust results underscore the importance of these predictors and the need to consider the neighborhood context in which homicide investigations occur in future studies of homicide clearances.

Surprisingly, results also revealed no effect of legal cynicism across any of the models. Although this finding was unexpected, previous research found that even though neighborhood residents may have negative attitudes toward the police, they are

still dependent on them for help (see, for example, Carr, Napolitano, & Keating, 2007; Stoutland, 2001). Furthermore, Goudriaan, Wittebrood, and Nieuwbeerta (2006) found that neighborhood social cohesion influenced reporting, but perceptions of police effectiveness did not have an effect. This is consistent with our supplemental analyses that found that social cohesion appears to be the driving force in community members' involvement in homicide clearances. Scholars who study clearance tend to explain lack of cooperation in terms of fear of retaliation (e.g., Regoeczi & Jarvis, 2013; Riedel & Jarvis, 1998), lack of trust in police (e.g., Kane, 2005; Puckett & Lundman, 2003; Warner, 2007), or both. It appears that in areas where residents have greater social cohesion and trust in each other, they are more willing to engage, despite any lack of trust in the police.

Finally, none of the case compositional variables reached significance in the first two models, which is somewhat surprising given the role of these factors in incident-level studies of homicide clearance. Although surprising, research tends to find less of an effect when considering the composition of homicide cases in a given area (i.e., the percent of homicides involving male victims) as opposed to a dummy variable indicating the victim was male in incident-level studies of homicide clearance (see, for example, Ousey & Lee, 2010; Petersen, 2017), which may also be the case here. However, percent White victims and percent firearms did become significant in Model 3, after low homicide neighborhoods were removed. Both the percent of homicide victims that were White and the percent of homicides committed with a firearm significantly increased the expected homicide clearance count. A comparison of the sample characteristics from the total sample to the reduced sample used in Model 3 reveals differences in the composition of homicide cases that occur in these two samples. Results reveal, homicides are much less likely to involve White victims and more likely to have been committed with a firearm in the reduced sample, which may be influencing the increase in significance in these two variables in Model 3. Specifically, there is a 24% reduction in the percent of homicides involving White victims and a 6% increase in the percent of homicides involving firearms from the full to the reduced sample. Perhaps in neighborhoods where homicides are more frequent, characteristics of the homicide incident, including both discretionary and nondiscretionary factors, become more pertinent to the investigation.

Conclusion

This article filled an important gap in the literature by theorizing and empirically testing the relationship between collective efficacy and homicide clearances in Chicago neighborhoods. The extant literature has established that collective efficacy has several positive effects on the community, including decreasing the negative effects of structural disadvantage on crime rates and public health issues (e.g., Browning & Cagney, 2002; Cohen, Finch, Bower, & Sastry, 2006). However, less is known about how this construct, incorporating a type of informal social control, may affect formal social control outcomes (e.g., arrest, clearance, prosecution; but see Kirk & Matsuda, 2011; Mustaine, Tewksbury, Corzine, & Huff-Corzine, 2012; Regoeczi & Jarvis, 2013,

for important exceptions). Part of the impetus behind this work was to advance theoretical understanding of collective efficacy by testing its effects on an outcome that has yet to be explored, homicide clearances. Furthermore, by using the same dataset (i.e., the PHDCN) and similar measures as previous tests of collective efficacy, the possibility that these findings are due to measurement specification errors is reduced, while also allowing the results to be more comparable with previous tests of collective efficacy (e.g., Kirk & Matsuda, 2011; Morenoff et al., 2001; Sampson et al., 1997). In addition, little research on the role that neighborhood context plays in police clearance of homicides is available in the literature. Therefore, this study served to enhance an overall understanding of factors that affect homicide clearances in an urban context.

Besides the theoretical and empirical contribution of the present study, the results of this research have practical implications as well. Despite recent advances in technology, crime clearance still hinges on information provided by witnesses and/or victims (see Braga & Dusseault, 2016; Lum & Nagin, 2017, for a similar argument). Therefore, and as documented in this research, focusing on social mechanisms that promote trust and cohesion between community members and engagement with police can have significant influences on crime clearance. With questions of where departmental resources should be allocated, it may be fruitful for departments to focus more time and money on enhancing the level of collective efficacy in the neighborhood, more so than investing money in additional technologies. In addition, researchers and the community should focus on ways that both police and neighborhood residents can foster, maintain, and enhance collective efficacy.

Considering important racial and ethnic differences in police–citizen relations in predominately African American and predominately Latino neighborhoods, it may also prove especially fruitful to explore the relationship between neighborhood context, collective efficacy, and homicide clearance rates in these neighborhoods. A consistent finding in much of the literature is that residents in predominately African American neighborhoods tend to distrust the police due to the style of policing in these neighborhoods as compared with predominately White neighborhoods (e.g., Anderson, 1999; Puckett & Lundman, 2003; Skogan, 2006). For example, Kochel (2015) found that African American residents in St. Louis County, Missouri, had lower views on procedural justice, less trust in police, and were less willing to cooperate with police. She also found that views on police legitimacy, procedural justice, and trust declined more sharply among African American residents after the shooting death of Michael Brown, particularly among African American residents in disadvantaged communities. In addition, Desmond, Papachristos, and Kirk (2016) recently found that crime reporting declined in Milwaukee following the beating of Frank Jude, especially among residents in African American neighborhoods. Research has also found that Latinos have unique relationships with police, due to factors such as anti-immigration sentiments and language barriers hindering successful relationships (e.g., Alderden & Lavery, 2007; Briggs & Opsal, 2012), which may also affect clearance. Surprisingly, legal cynicism did not reach significance in any of the models. It is likely that legal cynicism and lack of trust in police may be heightened in economically disadvantaged areas and areas with large minority populations (see, for example, Leovy, 2015,

narrative on the tensions between police and disadvantaged minority populations in Los Angeles County). Therefore, race-specific analyses may shed some light on these insignificant results and provide additional directions for future research.

Despite the contributions of the present research, a discussion of the limitations and subsequent directions for future research is warranted. First, this research did not account for spatial autocorrelation or the potential interdependency between neighboring communities, and previous studies have found that the level of collective efficacy in a neighborhood is related to the levels of collective efficacy in surrounding neighborhoods (e.g., Morenoff et al., 2001; Sampson, Morenoff, & Earls, 1999).

Second, these results are applicable to *homicide* clearances, and results are not generalizable to other crime types. Past research has found that the factors that affect clearance vary by crime type (e.g., Jarvis et al., 2016; Mustaine et al., 2012; Paré et al., 2007; Roberts, 2008). For example, Roberts (2008) found that community characteristics differentially affected clearance for sexual offenses compared with other types of nonsexual violent offenses. Homicides are not subject to reporting issues as readily as other crimes, and neighborhood residents may be more willing to intervene in more serious instances. As such, collective efficacy may play a very different role in police clearance of other types of crimes, and future research should consider its impact for other less serious crimes.

Third, because this research focused specifically on homicide clearance in Chicago neighborhoods in the early 1990s, results are not generalizable to other locales or other time periods. Several major changes occurred in the 1990s, including the implementation of community policing in Chicago in 1993 (Skogan, 2006), which could potentially affect the outcome. Because policing is largely reactive, especially when it comes to clearing crimes, police rely heavily on information from victims and witnesses. The potential impact of more proactive policing strategies, such as community policing, should be considered. Other major shifts occurred around this same time as well, including the unprecedented decline in violent crime rates through the 1990s (e.g., Blumstein & Wallman, 2006; Zimring, 2007). Research has demonstrated that there is some evidence of temporal variation in the importance of predictors of homicide clearance (e.g., Litwin & Xu, 2007). Therefore, future research should also test these arguments in other locales and time periods, which may show the findings here vary depending on historical or contextual conditions.

Finally, due to data limitations, this study did not control for organizational factors (e.g., police force size or department workload) which may affect homicide clearances. While models do include a self-reported victimization measure, the researchers acknowledge that this is a very rough proxy for workload and that errors in reporting victimization may be correlated with errors in homicide clearance. However, it was the best available proxy in the data that we had access to. It is likely that the number of police officers and amount of resources allocated to crime prevention and investigation vary greatly by neighborhood, even within the same jurisdiction (e.g., due to hot spot policing or other targeted policing initiatives). In addition, allocation of resources may also be influenced by collective efficacy providing an alternative explanation for the results obtained here. Despite this limitation, research tends to find that departmental

resources do not play a significant role in homicide clearance outcomes, regardless of measure used (e.g., Korosec, 2012; Litwin, 2004; Litwin & Xu, 2007; Ousey & Lee, 2010; Petersen, 2017; Puckett & Lundman, 2003; Xu, 2008).

Despite the above limitations, this research has contributed to the growing understanding of the positive effects of collective efficacy and has expanded our knowledge about the factors affecting police clearance of crimes in urban areas. Several avenues for future research were suggested. As such, the present research hopefully serves as a springboard for future inquiries in this and related lines of research.

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Notes

1. Neighborhood cluster, NC, and neighborhood are all used interchangeably.
2. A criticism of previous tests of collective efficacy is that studies sometimes measure the outcome variable at the same time or earlier than collective efficacy (see Hipp & Wo, 2015, for a discussion). Combining 1990 census data with PHDCN data from 1994-1995 and homicide clearance data for 1996-2000 establishes the correct temporal ordering between the predictor variables and the outcome variable.
3. Homicides may be cleared by exceptional means if the offender is known, but something precludes the police from making an arrest (e.g., the offender commits suicide or is being prosecuted for another offense in a different jurisdiction). The extant literature has debated whether exceptionally cleared homicides should be included in analyses (see, for example, Jarvis & Regoeczi, 2009; Riedel & Boulahanis, 2007); however this study includes homicides cleared by exceptional means because the data do not differentiate the two.
4. This is consistent with Sampson, Raudenbush, and Earls (1997) reliability of $r = .80$.
5. Analyses were also conducted leaving this NC in the models. Results are substantively similar to those presented here and available upon request to the first author.
6. Drawing on an anonymous reviewer's comment that a standard deviation increase in the economic disadvantage index appears to have an excessively large impact on the change in the expected homicide clearance count, we performed several supplemental analyses to explore this finding further, including an examination of a possible curvilinear relationship between economic disadvantage and homicide clearance, as well as robustness checks by removing NCs with extreme levels of economic disadvantage (i.e., those 2 and 3 standard deviations above the mean). Results did not reveal any evidence of a curvilinear relationship and the robustness checks produced results similar in magnitude to those presented

here. Supplemental analyses not reported here are available upon request. One possible reason for such a large effect may be that the standard deviation for economic disadvantage is quite large (71.81), particularly in comparison with the other variables in the models. Therefore, a very small percentage of NCs actually fall outside of 2 standard deviations from the mean (less than 3%).

7. We caution readers when interpreting the pseudo-R^2 value as this test statistic in count models does not have the same meaning as it does in traditional ordinary least squares (OLS) models (i.e., the proportion of variance explained by the independent variables in the model).

References

Alderden, M. A., & Lavery, T. A. (2007). Predicting homicide clearances in Chicago: Investigating disparities in predictors across different types of homicide. *Homicide Studies*, *11*, 115-132.

Anderson, E. (1999). *Code of the street: Decency, violence, and the moral life of the inner city*. New York, NY: W.W. Norton.

Armstrong, T. A., Katz, C. M., & Schnebly, S. M. (2015). The relationship between citizen perceptions of collective efficacy and neighborhood violent crime. *Crime & Delinquency*, *61*, 121-142.

Blumstein, A., & Wallman, J. (2006). *The crime drop in America* (2nd ed.). New York, NY: Cambridge University Press.

Borg, M. J., & Parker, K. F. (2001). Mobilizing law in urban areas: The social structure of homicide clearance rates. *Law & Society Review*, *35*, 435-466.

Braga, A. A., & Dusseault, D. (2016). Can homicide detectives improve homicide clearance rates? *Crime & Delinquency*, 63, 1-33.

Briggs, S., & Opsal, T. (2012). The influence of victim ethnicity on arrest in violent crimes. *Criminal Justice Studies: A Critical Journal of Crime, Law and Society*, *25*, 177-189.

Browning, C. R. (2009). Illuminating the downside of social capital: Negotiated coexistence, property crime, and disorder in urban neighborhoods. *American Behavioral Scientist*, *52*, 1556-1578.

Browning, C. R., & Cagney, K. A. (2002). Neighborhood structural disadvantage, collective efficacy, and self-rated physical health in an urban area. *Journal of Health and Social Behavior*, *43*, 383-399.

Browning, C. R., Feinberg, S. L., & Dietz, R. D. (2004). The paradox of social organization: Networks, collective efficacy, and violent crime in urban neighborhoods. *Social Forces*, *83*, 503-534.

Carr, P. J., Napolitano, L., & Keating, J. (2007). We never call the cops and here is why: A qualitative examination of legal cynicism in three Philadelphia neighborhoods. *Criminology*, *45*, 445-480.

Carter, D. L., & Carter, J. G. (2016). Effective police homicide investigations: Evidence from seven cities with high clearance rates. *Homicide Studies*, *20*, 150-176.

Cohen, D. A., Finch, B. K., Bower, A., & Sastry, N. (2006). Collective efficacy and obesity: The potential influence of social factors on health. *Social Science & Medicine*, *62*, 769-778.

Davis, R. C., Jensen, C. J., Burgette, L., & Burnett, K. (2014). Working smarter on cold cases: Identifying factors associated with successful cold case investigations. *Journal of forensic sciences, 59*(2), 375-382.

Desmond, M., Papachristos, A. V., & Kirk, D. S. (2016). Police violence and citizen crime reporting in the Black community. *American Sociological Review*, *81*, 857-876.

Federal Bureau of Investigation. (1997). *Crime in the United States: Uniform Crime Reports, 1996*. Washington, DC: U.S. Department of Justice, U.S. Government Printing Office.

Federal Bureau of Investigation. (1998). *Crime in the United States: Uniform Crime Reports, 1997*. Washington, DC: U.S. Department of Justice, U.S. Government Printing Office.

Federal Bureau of Investigation. (1999). *Crime in the United States: Uniform Crime Reports, 1998*. Washington, DC: U.S. Department of Justice, U.S. Government Printing Office.

Federal Bureau of Investigation. (2000). *Crime in the United States: Uniform Crime Reports, 1999*. Washington, DC: U.S. Department of Justice, U.S. Government Printing Office.

Federal Bureau of Investigation. (2001). *Crime in the United States: Uniform Crime Reports, 2000*. Washington, DC: U.S. Department of Justice, U.S. Government Printing Office.

Federal Bureau of Investigation. (2016). *Crime in the United States: Uniform Crime Reports, 2015*. Washington, DC: U.S. Department of Justice, U.S. Government Printing Office.

Felson, M. (1998). *Crime and everyday life* (2nd ed.). Thousand Oaks, CA: Pine Forge Press.

Ganley, J. B. (2016). *From small towns to large cities: A comparative study looking at the factors affecting homicide clearance rates in two types of Colorado geographic areas* (Undergraduate honors theses). University of Colorado Boulder.

Goudriaan, H., Wittebrood, K., & Nieuwbeerta, P. (2006). Neighbourhood characteristics and reporting crime effects of social cohesion, confidence in police effectiveness and socioeconomic disadvantage. *British Journal of Criminology*, *46*, 719-742.

Greenwood, P. W., Chaiken, J. M., & Petersilia, J. (1977). *The criminal investigation process*. Lexington, MA: D.C. Health.

Hawk, S. (2015). *A multi-method examination of homicide investigations on case outcomes* (Doctoral dissertation). Georgia State University, Atlanta.

Hipp, J. R., & Wo, J. C. (2015). Collective efficacy and crime. *International Encyclopedia of the Social & Behavioral Sciences*, *2*, 169-173.

Horne, C. (2004). Collective benefits, exchange interests, and norm enforcement. *Social Forces*, *82*, 1037-1062.

Jackall, R. (2005). *Street stories: The world of police detectives*. Cambridge, MA: Harvard University Press.

Jarvis, J. P., Mancik, A., & Regoeczi, W. C. (2016). Police responses to violent crime: Reconsidering the mobilization of law. *Criminal Justice Review*, *42*, 5-25.

Jarvis, J. P., & Regoeczi, W. C. (2009). Homicide clearances: An analysis of arrests versus exceptional outcomes. *Homicide Studies*, *13*, 174-188.

Jiao, A. Y. (2007). Explaining homicide clearance: An analysis of Chicago homicide data 1965-1995. *Criminal Justice Studies*, *20*, 3-14.

Kane, R. J. (2005). Compromised police legitimacy as a predictor of violent crime in structurally disadvantaged communities. *Criminology*, *43*, 469-498.

Keel, T. G., Jarvis, J. P., & Muirhead, Y. E. (2009). An exploratory analysis of factors affecting homicide investigations: Examining the dynamics of murder clearance rates. *Homicide Studies*, *13*, 50-68.

Kennedy, P. (1998). *A guide to econometrics*, 4th edition. Cambridge, MA: MIT Press.

Kirk, D. S., & Matsuda, M. (2011). Legal cynicism, collective efficacy, and the ecology of arrest. *Criminology*, *49*, 443-472.

Kirk, D. S., & Papachristos, A. V. (2011). Cultural mechanisms and the persistence of neighborhood violence. *American Journal of Sociology, 116*(4), 1190-1233.

Kochel, T. R. (2015). *Assessing the initial impact of the Michael Brown shooting and police and public responses to it on St Louis County residents' views about police*. Southern Illinois University Carbondale.

Korosec, L. (2012). *The changing nature of homicide and its impact on homicide clearance rates: A quantitative analysis of two trends from 1984-2009* (Master's thesis). The University of Western Ontario, London, Canada.

Krivo, L. J., & Peterson, R. D. (1996). Extremely disadvantaged neighborhoods and urban crime. *Social Forces*, *75*, 619-650.

Land, K. C., McCall, P. L., & Cohen, L. E. (1990). Structural covariates of homicide rates: Are there any invariances across time and social space? *American Journal of Sociology*, *95*, 922-963.

Lee, C. (2005). The value of life in death: Multiple regression and event history analyses of homicide clearance in Los Angeles County. *Journal of Criminal Justice*, *33*, 527-534.

Leovy, J. (2015). *Ghettoside: A true story of murder in America*. New York, NY: Spiegel & Grau.

Litwin, K. J. (2004). A multilevel multivariate analysis of factors affecting homicide clearances. *Journal of Research in Crime & Delinquency*, *41*, 327-351.

Litwin, K. J., & Xu, Y. (2007). The dynamic nature of homicide clearances: A multilevel model comparison of three time periods. *Homicide Studies*, *11*, 94-114.

Lum, C., & Nagin, D. S. (2017). Reinventing American policing. *Crime and Justice*, *46*, 339-393.

Lundman, R. J., & Myers, M. (2012). Explanations of homicide clearances: Do results vary dependent upon operationalization and initial (time 1) and updated (time 2) data? *Homicide Studies*, *16*, 23-40.

Maguire, E. R., King, W. R., Johnson, D., & Katz, C. M. (2010). Why homicide clearance rates decrease: Evidence from the Caribbean. *Policing & Society*, *20*, 373-400.

McEwen, T., & Regoeczi, W. (2015). Forensic evidence in homicide investigations and prosecutions. *Journal of Forensic Sciences*, *60*, 1188-1198.

Minnesota Population Center. (2011). *National Historical Geographic Information System: Version 2.0*. Minneapolis: University of Minnesota. Available from http://www.nhgis.org

Morenoff, J. D., Sampson, R. J., & Raudenbush, S. W. (2001). Neighborhood inequality, collective efficacy, and the spatial dynamics of urban violence. *Criminology*, *39*, 517-558.

Mouzos, J., & Muller, D. (2001). *Solvability factors of homicide in Australia: An exploratory analysis*. Canberra: Australian Institute of Criminology.

Mustaine, E. E., Tewksbury, R., Corzine, J., & Huff-Corzine, L. (2012). Can social disorganization or case characteristics explain sexual assault case clearances? *Victims and Offenders*, *7*, 255-278.

Osgood, D. W. (2000). Poisson-based regression analysis of aggregate crime rates. *Journal of Quantitative Criminology*, *16*, 21-43.

Ousey, G. C., & Lee, M. R. (2010). To know the unknown: The decline in homicide clearance rates, 1980-2000. *Criminal Justice Review*, *35*, 141-158.

Paré, P., Felson, R. B., & Ouimet, M. (2007). Community variation in crime clearance: A multilevel analysis with comments on assessing police performance. *Journal of Quantitative Criminology*, *23*, 243-258.

Petersen, N. (2017). Neighbourhood context and unsolved murders: The social ecology of homicide investigations. *Policing & Society*, *27*, 372-392.

Puckett, J. L., & Lundman, R. J. (2003). Factors affecting homicide clearances: Multivariate analysis of a more complete conceptual framework. *Journal of Research in Crime & Delinquency*, *40*, 171-193.

Regoeczi, W. C., & Jarvis, J. P. (2013). Beyond the social production of homicide rates: Extending social disorganization theory to explain homicide case outcomes. *Justice Quarterly*, *30*, 983-1014.

Regoeczi, W. C., Kennedy, L. W., & Silverman, R. A. (2000). Uncleared homicides: A Canada/United States comparison. *Homicide Studies*, *4*, 135-161.

Reisig, M. D., & Cancino, J. M. (2004). Incivilities in nonmetropolitan communities: The effects of structural constraints, social conditions, and crime. *Journal of Criminal Justice*, *32*, 15-29.

Reiss, A. J. (1971). *The police and the public*. New Haven, CT: Yale University Press.

Riedel, M., & Boulahanis, J. G. (2007). Homicides exceptionally cleared and cleared by arrest: An exploratory study of police/prosecutor outcomes. *Homicide Studies*, *11*, 151-164.

Riedel, M., & Jarvis, J. P. (1998). The decline of arrest clearances for criminal homicide: Causes, correlates, and third parties. *Criminal Justice Policy Review*, *9*, 279-306.

Riedel, M., & Rinehart, T. A. (1996). Murder clearances and missing data. *Journal of Crime & Justice*, *19*, 83-102.

Roberts, A. (2008). The influences of incident and contextual characteristics on crime clearance of nonlethal violence: A multilevel event history analysis. *Journal of Criminal Justice*, *36*, 61-71.

Rydberg, J., & Pizarro, J. M. (2014). Victim lifestyle as a correlate of homicide clearance. *Homicide Studies*, *18*, 342-362.

Sampson, R. J. (2008). Collective efficacy theory: Lessons learned and directions for future inquiry. In F. T. Cullen, J. P. Wright, & K. R. Blevins (Eds.), *Taking stock: The status of criminological theory* (pp. 149-167). New Brunswick, NJ: Transaction Publishers.

Sampson, R. J. (2012). *Great American city: Chicago and the enduring neighborhood effect*. Chicago, IL: The University of Chicago Press.

Sampson, R. J., & Groves, W. B. (1989). Community structure and crime: Testing social-disorganization theory. *American Journal of Sociology*, *94*, 774-802.

Sampson, R. J., Morenoff, J. D., & Earls, F. (1999). Beyond social capital: Spatial dynamics of collective efficacy for children. *American Sociological Review*, *64*, 633-660.

Sampson, R. J., Raudenbush, S. W., & Earls, F. (1997). Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science*, *277*, 918-924.

Schroeder, D. A., & White, M. D. (2009). Exploring the use of DNA evidence in homicide investigations: Implications for detective work and case clearance. *Police Quarterly*, *12*, 319-342.

Shaw, C. R., & McKay, H. D. (1942). *Juvenile delinquency and urban areas*. Chicago, IL: The University of Chicago Press.

Shaw, C. R., Zorbaugh, F. M., McKay, H. D., & Cottrell, L. S. (1929). *Delinquency areas: A study of the geographic distribution of school truants, juvenile delinquents, and adult offenders in Chicago*. Chicago, IL: The University of Chicago Press.

Skogan, W. G. (2006). *Police and community in Chicago: A tale of three cities*. New York, NY: Oxford University Press.

Smith, D. A. (1986). The neighborhood context of police behavior. In A. J. Reiss Jr., & M. Tonry (Eds.), *Communities and crime* (pp. 313-341). Chicago, IL: The University of Chicago Press.

Stoutland, S. E. (2001). The multiple dimensions of trust in resident/police relations in Boston. *Journal of Research in Crime & Delinquency*, *38*, 226-256.

Terrill, W., & Reisig, M. D. (2003). Neighborhood context and police use of force. *Journal of Research in Crime & Delinquency*, *40*, 291-321.

Warner, B. D. (2007). Directly intervene or call the authorities? A study of forms of neighborhood social control within a social disorganization framework. *Criminology*, *45*, 99-129.

Wellford, C., & Cronin, J. (1999). *An analysis of variables affecting the clearance of homicides: A multisite study*. Washington, DC: Justice Research and Statistics Association.

Westmarland, L. (2013). "Snitches get stitches": U.S. homicide detectives' ethics and morals in action. *Policing & Society*, *23*, 311-327.

Williams, K. R., & Guerra, N. G. (2011). Perceptions of collective efficacy and bullying perpetration in schools. *Social Problems*, *58*, 126-143.

Wirth, L. (1938). Urbanism as a way of life. *American Journal of Sociology*, *44*, 1-24.

Wolfgang, M. E. (1958). *Patterns in criminal homicide*. Philadelphia: University of Pennsylvania Press.

Xu, Y. (2008). Characteristics of homicide events and the decline in homicide clearance: A longitudinal approach to the dynamic relationship, Chicago 1966-1995. *Criminal Justice Review*, *33*, 453-479.

Zimring, F. E. (2007). *The great American crime decline*. New York, NY: Oxford University Press.

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