# Abstract

*Collective efficacy is a prominent explanation for neighborhood crime concentrations. Just as crime is concentrated in particular neighborhoods, within neighborhoods crime is concentrated in particular criminogenic locations. Research suggests criminogenic locations are determined by features of the built environment. This study links collective efficacy with situational opportunity to propose that collective efficacy facilitates the removal of criminogenic features of the built environment. I test this by examining associations (1) between past collective efficacy and present criminogenic features of the built environment, and (2) between those built environment features and crime, net of present collective efficacy. These are modeled using piecewise structural equations with generalized linear mixed-effect regressions on data from 1,641 blocks in 343 Chicago neighborhoods. Five types of police-reported crime (N=424,698) are modeled using eight block-level built environment features in the 2003 Chicago Community Area Health Study (N=3,105) and neighborhood collective efficacy from the CCAHS and 1995 PHDCN Community Survey (N=8,782). Findings suggest neighborhoods with high collective efficacy maintain low rates of crime in part by limiting criminogenic built environment features, in particular abandoned buildings. This crime control pathway is important because changes to the built environment are long-lasting and reduce the need for future interventions against crime.*

# Introduction

Crime is highly concentrated in particular urban neighborhoods (Shaw & McKay, 1969/1942). Variation in collective efficacy—conceptualized as the general problem-solving capacity of neighborhoods—is a prominent explanation for neighborhood differences in crime (Sampson, 2012; Sampson, Raudenbush, & Earls, 1997). Informal social control, such as resident monitoring and interventions against crime and disorder, is assumed to be the primary mechanism by which collective efficacy reduces neighborhood crime. Importantly, collective efficacy measures the perceived capacity for such social control actions, rather than realized actions, which occur only when an offense is attempted (Sampson, 2012, pp. 156–160). Even when interventions are not observed, the perceived certainty of intervention exerts a deterrent effect on crime in neighborhoods with high collective efficacy. Like the classic social disorganization construct it is intellectually descended from, collective efficacy mediates much of the relationship between neighborhood sociodemographic structure and crime (Sampson, Raudenbush, & Earls, 1997).

Just as crime is concentrated in particular neighborhoods, within neighborhoods crime is concentrated in particular locations—hot spots (Sherman, Gartin, & Buerger, 1989; Weisburd, Groff, & Yang, 2012). The locations of hot spots are largely determined by the presence of specific features of the built environment which are criminogenic in the sense that they provide opportunities for crime (St. Jean, 2007; Wilcox & Cullen, 2018). The literature on situational opportunity and environmental criminology is rich with examples of criminogenic contexts, such as vacant or abandoned buildings, venues for alcohol sales, commercial properties and mixed land use, parks and recreation facilities, and parking lots (see Wilcox & Cullen, 2018 for a review).

Residents, rightly or not, associate certain features of the environment such as abandoned buildings with crime and disorder and consequently view them as problematic (Innes, 2004). As a problem-solving capacity of neighborhoods, collective efficacy may facilitate actions to remediate, remove, or prevent the development of these features. In contrast to the more commonly studied informal control interventions to control unwanted behavior, these actions are interventions to control contexts perceived to precipitate unwanted behavior. If collective efficacy promotes the control of criminogenic features of the built environment, then the concentration of these features should partially explain the effect of collective efficacy on crime.

Accordingly, this work examines how collective efficacy is related to the distribution of criminogenic features of the built environment, and the contribution of those features to rates of crime. I first present a framework that integrates collective efficacy with place-based situational opportunity, then test hypotheses from this framework with a multilevel longitudinal research design using data from Chicago on block-level built environment features and neighborhood-level collective efficacy. My findings suggest neighborhoods with high collective efficacy maintain low rates of crime in part by limiting the presence of built environment features that promote criminal opportunities.

## The built environment and crime

The built environment has long been recognized as a one of the most important predictors of crime (e.g. Jacobs, 1992; Jeffery, 1977; Newman, 1978). While the built environment influences many forms of crime, this research focuses specifically on crimes defined as direct-contact predatory violations—acts in which an offender intentionally directly and physically takes or damages another individual or their property (Cohen & Felson, 1979). By structuring the routine activities of people, the built environment influences the requisite components of these predatory criminal acts: the convergence in time and space of motivated offenders, suitable targets, and the absence of capable guardians (Cohen & Felson, 1979; see also Brantingham & Brantingham, 1981).

Many features of the built environment are potentially criminogenic, but, importantly, they are not purely criminogenic: a park may provide recreational options to families, or provide concealment for criminal activities, or both, perhaps depending on the time of day. In this way, potentially criminogenic features of the built environment also serve non-criminal purposes for residents and visitors, and thus are not perceived solely as problematic. Simply removing all features which might facilitate crime is not a valid solution, because they are necessary for the routine activities of people. Crime tends to be higher in the presence of most non-residential features of the built environment simply because more people make use of those spaces (Wilcox & Eck, 2011). Crime cannot exit in a vacuum, but neither can people. Control of crime facilitated by the built environment thus exists in tension with the legitimate uses of space. Criminogenic features perceived to offer little benefit to residents will likely be subject to stronger removal efforts.

Some features of the built environment, such as abandoned buildings and vacant lots, are commonly considered forms of physical disorder (e.g., Sampson & Raudenbush, 1999). The broken windows thesis posits that disorder increases crime because it serves as a signal of weak social control, emboldening potential offenders and driving others to withdraw from public spaces to avoid victimization (Wilson & Kelling, 1982). In the terms of routine activities, broken windows posits that disorder increases crime by signaling to potential offenders an absence of capable guardianship. Because it is based on signaling social control capability, this mechanism is assumed to increase the likelihood of offending of almost any kind. Support for a general criminogenic effect of disorder is weak (Lanfear, Matsueda, & Beach, 2020; Sampson & Raudenbush, 1999). Further, rather than being interpreted as a signal of weak social control, the meaning of disorder appears to be ambiguous (Innes, 2004; St. Jean, 2007). For example, St. Jean (2007) found residents interpreted physical disorder as a sign of neglect by institutional actors responsible for sanitation or code enforcement, rather than as a sign of weak social control.

In contrast to the signaling mechanism of broken windows, the present work posits that features of the built environment—some of which may be perceived as disorder—facilitate crime by generating opportunities characterized by the convergence of likely offenders and suitable targets in the absence of capable guardians. While some disorderly contexts may provide criminal opportunities—thus increasing crime if potential offenders recognize and exploit them—many provide no criminal opportunities (or may even be the result of crimes)—thus failing to promote crime.

Unlike the signaling mechanism of broken windows in which any disorder signals low social control, a given opportunity typically applies only to specific crimes. Situational opportunity theories of crime—including routine activities theory—posit that different contexts generate opportunities for different types of crime (Cohen & Felson, 1979; Wilcox & Cullen, 2018). For example, an unattended home provides an opportunity for burglary, but not homicide or robbery, because no one is home. Similarly, criminogenic effects of built environment features are specific to particular criminal opportunities. For example, vacant lots and abandoned buildings facilitate homicide and gun violence by acting as illicit firearm storage (MacDonald, Branas, & Stokes, 2019), liquor stores and bars precipitate assaults and provide vulnerable targets for robberies (Pridemore & Grubesic, 2012; Wheeler, 2019), and commercial or mixed land uses—as well as parking lots—impede surveillance and interaction, and provide targets for robbery and property crime (Sampson & Raudenbush, 1999; Wo, 2019). Some features may, like many non-residential properties, promote a wide range of crimes due simply to increasing the density of people present (Wilcox & Eck, 2011) or, like recreation facilities, by promoting unstructured socializing of youth (Osgood, Wilson, O’Malley, Bachman, & Johnston, 1996; Weisburd, Morris, & Groff, 2009). These are, of course, only a selection of examples. The literature on opportunity and the built environment is voluminous (Wilcox & Cullen, 2018).

These criminogenic built environment characteristics may even be more consequential than factors like residents’ capacity for social control. For example, St. Jean’s (2007) interviews with active offenders indicate some were willing to endure repeated confrontations with residents to continue operating in locations lucrative for drug dealing and robbery. In this way, the built environment can be a more important consideration than residents’ social control capacity—their collective efficacy. An outstanding question, and the focus of this work, is the degree to which collective efficacy is related to the distribution of these criminogenic features of the built environment.

## Control of the built environment

The built environment is shaped by the actions of local government in conjunction with developers and property owners (Logan & Molotch, 2007). Neighborhood residents may work collectively to control crime by removing, remediating, and preventing development of features that are perceived to present criminal opportunities. In this way, residents can use their economic, social, and political capital to influence external institutions and constrain criminal opportunities. While prominent research in community social control acknowledges the role of institutional linkages in shaping neighborhood conditions (e.g., Bursik & Grasmick, 1993; Sampson, 2012), the role of the built environment has not been specified within a general collective efficacy and situational opportunity framework.

Action to alter the built environment to prevent or remove criminogenic features is likely dependent on connections with external institutions and actors such as developers and policymakers. Even where the actors responsible for a given criminogenic feature are themselves neighborhood residents—such as the owner of a problem bar or overgrown vacant lot—external institutions with formal authority to fine owners or seize their property provide a point of leverage for collective action (e.g., Carr, 2005, pp. 121–123). The social disorganization tradition—from which the collective efficacy perspective emerged—has long recognized the importance of the community’s relationship to external actors. For example, in the systemic model of social disorganization, disorganized neighborhoods are characterized by an absence of connections to and influence over external institutions, such as city government (Bursik & Grasmick, 1993). Collective efficacy is thought to predict political mobilization to influence external institutions (Sampson, 2012, pp. 152–153), and one of the most commonly used indicators of collective efficacy in crime research is expectations that residents would organize to defend a fire station (or library) from closure (e.g., Sampson, Raudenbush, & Earls, 1997). This describes collective political action to influence local government to maintain an existing beneficial built environment feature.

Informal social control and control of the built environment are parallel forms of problem-solving which may emerge from the same latent capacity for action. Collective efficacy activates as informal social control when residents perceive nuisance or criminal behavior—and they believe informal social control can address the problem. When residents perceive features of the built environment as the source of criminal behavior or other threats, they sometimes engage in direct clean-up and remediation efforts which are analogous to the direct interventions associated with informal social control (Kelling & Coles, 1996). In other cases, however, collective efficacy activates as political action to influence external actors with authority to address the problem. For example, Einstein, Glick, and Palmer (2020) observed residents of a wealthy neighborhood fighting to prevent construction of a low-income housing development by lodging complaints in zoning board meetings, filing lawsuits, and petitioning officials. The residents described this as action on behalf of their community to protect it from crime, neighborhood change, and harm to property values. This represents an activation of collective efficacy in the form of political action. Other examples of actions directed at external institutions include protests (Rabrenovic, 1996) and invocations of regulatory agencies (Carr, 2005).

An important characteristic of collective efficacy is that it represents a capacity for social control actions rather than the frequency of those actions. Collective efficacy is assumed to reduce crime not only by promoting interventions but also through a deterrent mechanism (Sampson, 2012, pp. 159–160): Individuals are deterred from attempting offenses in highly efficacious neighborhoods because they perceive interventions by residents to be likely. A similar mechanism may operate with regard to the built environment. Efficacious neighborhoods can turn attempts at development into extended, costly battles (e.g., Einstein, Glick, & Palmer, 2020). If developers and city officials anticipate a particular neighborhood will be highly resistant, they may be unlikely to consider that neighborhood for their development. When a development is undesirable to residents but its location is flexible—a jail for example—disadvantaged neighborhoods become the default locations of first consideration (Logan & Molotch, 2007, p. 113). In this way, absent any observed political action, collective efficacy can still prevent the emergence of features residents perceive as undesirable, some of which are likely criminogenic (but many which are not, e.g. Bursik, 1989).

If collective efficacy impacts the ability of communities to influence the built environment for crime control purposes, then features of the built environment should mediate the effect of collective efficacy on crime over long periods of time. Unlike informal and formal control which operate immediately to inhibit crime, the slow pace of change in the built environment makes it a subtle and stable method of crime control. Neighborhoods with high collective efficacy in the past may exhibit low crime in the present because they prevented the emergence of criminogenic features. Given changes to the built environment are slow and cumulative, the built environment should be a mediator with regard to crime only for past collective efficacy. Further, if past collective efficacy impacts the built environment, which in turn impacts present collective efficacy, then change in the built environment is a mechanism by which collective efficacy is propagated over time and may serve as a point of intervention to bolster collective efficacy. This may occur if some features foster social ties and cohesion—building blocks of collective efficacy—by increasing interaction between residents (Small & Adler, 2019).

The collective action of residents is not, of course, the only means by which features of the built environment change in neighborhoods. The built environment of neighborhoods also responds to conditions in the political economy of the city and region. Rising (or declining) local property values, or the anticipation of rising (or declining) local property values, leads to changes in behavior by external actors like developers. External actors seeking to maximize the value of their property holdings for investment purposes often operate at odds with residents focused on maximizing the livability of their homes and neighborhoods (Logan & Molotch, 2007). Neighborhoods with organized, wealthy, and/or politically influential residents—those more likely to be collectively efficacious—more easily resist changes which compromise their perceived quality of life (Logan & Molotch, 2007). Einstein et al.’s (2020) neighborhood resistance against affordable housing provides an example. Disadvantaged neighborhoods—those less likely to be collectively efficacious—are more vulnerable to actions by outside actors looking to maximize their investments at the cost of resident quality of life. This includes non-resident owners of dilapidated apartments or poorly regulated bars that extract money from neighborhoods with little concern for residents (e.g., Desmond, 2016; Eck & Madensen, 2018). As a result, while the built environment of neighborhoods is subject to powerful outside forces, the ability of those outside forces to enact their will is in large part dependent on neighborhood socioeconomic structure and capacity for collective action.

# Approach

Based on this theoretical framework, I test the following hypotheses:

1. Features of the built environment facilitate crime by promoting convergences of potential offenders and suitable targets in the absence of capable guardians. Specifically:
   1. Features characterized by valuable or unguarded property or people carrying valuable property, including commercial destinations, mixed land use, parking lots, will promote property crime (including robbery).
   2. Features which reduce inhibitions, precipitate conflicts, or conceal weapons and illicit market transactions, such as abandoned buildings, bars, and vacant lots, will promote violence.
   3. Non-residential features in general—and recreation facilities in particular—may promote crime by increasing the number of people present at any given time.
2. Past collective efficacy reduces the presence of criminogenic features of the built environment.
3. Criminogenic features of the built environment reduce collective efficacy.

*Figure 1 about here*

Figure 1 depicts these hypotheses graphically. For simplicity, exogenous adjustment variables like neighborhood sociodemographic structure are omitted. A basic assumption of these hypotheses is that collective efficacy is negatively related to crime in the short term (path A). This is well-supported in the literature though some studies, in particular panel designs, find null effects, which may be a function of insufficient variation over time in collective efficacy (Lanfear, Matsueda, & Beach, 2020). Testing this direct effect is not a focus of the present study but the analysis here does serve as a replication of past research. If hypotheses 1 and 2 (or 1 and 3) are both supported (if paths H1 and H2 are nonzero), then criminogenic built environment features are confounders that, when omitted, exaggerate the contemporaneous effect of collective efficacy on crime. It is possible the direct effects of collective efficacy on crime (A) may be greatly, or even fully, attenuated once adjusting for features of the built environment. Even if this were the case, if hypothesis 2 is supported, it would suggest collective efficacy is still relevant to crime control, through the mechanism of control of the built environment rather than the assumed primary mechanism of informal social control.

While this study proposes a causal relationship between collective efficacy and crime via the built environment (hypotheses 1 and 2 combined), this is difficult to test. At the very least, there are four problems: (1) sequential ignorability, (2) reciprocal relationships between collective efficacy and the built environment, (3) selection in built environment features, and, less significantly, (4) task specificity of collective efficacy. I summarize these briefly here.

First, collective efficacy and the built environment are not randomly assigned characteristics of neighborhoods. Establishing causal mediation—the effect of past collective efficacy on present crime via the present built environment—requires strong assumptions about sequential ignorability: assignment of both treatment (collective efficacy) and mediator (built environment) must be ignorable conditional on observed covariates (Robins & Greenland, 1992). That is, one must make the assumption that all relevant covariates are included in the equations predicting both the built environment features and crime. These conditions are unlikely to hold within the complex system of an urban neighborhood. A further complication is the presence of multiple correlated mediators (i.e. the built environment features) which makes statistical tests of mediation challenging (VanderWeele, 2015). Consequently, the mediated effects, as well as path H1 from the built environment to crime, are difficult to identify. The result of this is that we can more convincingly test for the presence of conditional direct effects—such as collective efficacy on the built environment—than for the indirect (mediated) effects—collective efficacy on crime via the built environment—which require stronger assumptions to test.

Second, it is likely that some built environment conditions foster collective efficacy, creating a positive feedback loop over time (hypothesis 3). For example, successful removal or remediation of criminogenic features likely makes regulating the neighborhood easier by presenting fewer criminal opportunities while emboldening residents to undertake more efforts in the future as successes foster efficacy. Some features of the built environment may also increase social interaction that in turn strengthens collective efficacy (Small & Adler, 2019). Endogeneity of this sort will bias estimates upward. Provided repeated observations of neighborhoods, this may be addressed with longitudinal models. In the present case, only neighborhood collective efficacy is measured at two time points, and not block-level crime or the built environment, preventing use of a conventional panel model. I address this problem by predicting built environment features using past collective efficacy, and predicting present collective efficacy with those present built environment features. This makes the assumption that the pathway from collective efficacy to the built environment operates over a longer lag than the opposite pathway, which is assumed to be approximately immediate, as residents rapidly adapt to changes in the physical environment.

Third, there is a risk of selection bias if not all neighborhoods are at risk for having certain criminogenic features of the environment. For example, an affluent and predominantly residential neighborhood may not be viewed as a potential location for a bar or liquor store, so no collective action is conceivably needed to prevent the development. Logan and Molotch (2007) describe the development of urban spaces as the result of an interaction between the political economy of metropolitan areas and neighborhood characteristics—including political capital of residents. Investment and consequent development in neighborhoods are related to current and historical structural characteristics and the relative position compared to other neighborhoods in the city (Dreier, Mollenkopf, & Swanstrom, 2014; Logan & Molotch, 2007). Unobserved factors such as public infrastructure, zoning, and present or anticipated land values may influence development of the built environment. For the present analysis, this is problematic if the assignment of built environment features to places is not ignorable conditional on included measures like sociodemographic structures.

There is potentially another related problem. The average treatment effect of a given feature of the built environment is not identified if, for any given strata of the population, there is a probability of zero (or one) of that feature being present. These analyses thus make the strong assumptions that assignment of built environment features is essentially random conditional on the covariates and that the probability of each feature arising is not either one or zero at any level of the covariates.

Fourth, and finally, collective efficacy is task specific (Sampson, Raudenbush, & Earls, 1997). Conventional measures of collective efficacy are designed to capture informal social control capacity. However, this study is concerned with residents’ capacity to control the built environment, which likely occurs primarily via political action. I expect these factors will be strongly correlated, in part because one common indicator of collective efficacy is expectations residents would intervene to protect either a fire station or library—positive built environment features. That indicator describes actions to control the built environment. Nonetheless, I expect the standard measure of collective efficacy to be more strongly associated with crime directly—implicitly via informal social control—than indirectly via the built environment. This may attenuate the estimated effect of collective efficacy on the built environment.

# Data

This analysis uses data from the community survey in the 2001 through 2003 Chicago Community Area Health Study (CCAHS) (House et al., 2011). The CCAHS was administered to a stratified, multistage sample of 3,105 adults living in Chicago. This survey provides measures of collective efficacy and the structural variables of social disorganization at the neighborhood cluster level—the primary stratification unit for the survey. These clusters were originally created for the 1995 Project in Human Development in Chicago Neighborhoods (PHDCN) to represent Chicago neighborhoods (Earls, Brooks-Gunn, Raudenbush, & Sampson, 1999). Each cluster is a set of, on average, three geographically contiguous census tract. The median cluster is 0.50 square miles in area, and 90% of clusters are between 0.19 and 1.61 square miles.[[1]](#footnote-25) These clusters were constructed to maximize ecological validity using a combination of cluster analyses of census-recorded sociodemographic characteristics to ensure internal homogeneity, natural boundaries from prominent geographical features (e.g. freeways), and local knowledge of Chicago neighborhoods (Sampson, 2012, pp. 78–80; Sampson, Raudenbush, & Earls, 1997, p. 919). Hereafter I use the term neighborhood to refer to these neighborhood cluster units. For brevity, I also refer to measures from the 2001-2003 CCAHS as 2003 measures.

In line with past research in this area, I measure collective efficacy as a combination of resident expectations their neighbors would intervene against different types of deviance—but also to protect a library or fire station threatened with defunding—and perceptions of cohesion and trust—such as shared values in the neighborhood (Sampson, Raudenbush, & Earls, 1997). As is common in this literature, my measure of collective efficacy is an empirical Bayes estimate derived from a multilevel measurement model that adjusts resident-perceived collective efficacy for sociodemographic characteristics of respondents and conservatively shrinks estimates toward zero where interrater reliability is lower (Sampson, Raudenbush, & Earls, 1997). See the appendix for indicators and reliabilities.

Neighborhood sociodemographic structure is a primary determinant of crime rates, and collective efficacy mediates a large portion of this relationship (Sampson, Raudenbush, & Earls, 1997). To properly specify models of collective efficacy and crime, I constructed measures of neighborhood sociodemographic structure. Following past research in this area (e.g., Sampson, Raudenbush, & Earls, 1997), I generate a parsimonious set of measures using an alpha-scoring oblique factor rotation of nine year 2000 census indicators from the Longitudinal Tract Data Base (LTDB) (Logan, Xu, & Stults, 2014). The LTDB normalizes census tract boundaries over time to ensure measures in longitudinal studies describe the same units over time. Despite being conducted in 2001-2003, the CCAHS data is identified to year 1990 census boundaries. The LTDB was used to ensure the survey and census data describe the same geographical units. The indicators were chosen to match those used by Sampson, Raudenbush, and Earls (1997) to operationalize 1990 neighborhood social-structural characteristics, though one of these indicators (percent families on public assistance) was not available in the LTDB.[[2]](#footnote-26) Based on the factors each indicator loads on, I label the factors disadvantage, stability, and Hispanic / immigrant population. These factors are analogous to the classic structural antecedents of social disorganization and its modern derivatives (Bursik & Grasmick, 1993; Shaw & McKay, 1969/1942). See the appendix for a list of indicators and their factor loadings.

The CCAHS also provides systematic social observation (SSO) measures of a random sample of census blocks within each neighborhood cluster—almost exclusively the same blocks in which respondents resided. The SSO for the CCAHS was conducted by survey interviewers walking the perimeter of the sampled block twice and recording what they observe on each block face via a checklist. A block face is a single side of the street between two intersections that form corners of a block; a rectangular block, for example, has four block faces. Observers recorded data for block faces on the focal block, as well as block faces on adjacent blocks that face the focal block. In this case, a square block would have eight block face observations consisting of its own four block faces and the four faces across each street adjacent to the block. The indicators recorded cover a broad range of features describing health hazards, the built environment, and disorder (see House et al., 2011). The SSO for the CCAHS covers all 343 neighborhood clusters, however only 1,641 of Chicago’s approximately 20,000 census blocks are represented. Figure 2 depicts the sampled blocks and neighborhood clusters. Note that most sampled blocks are isolated or adjacent to few other sampled blocks.

*Figure 2 about here*

From the SSO, I obtain measures of all built environment features: abandoned buildings, bars, commercial destinations, liquor stores, mixed land use, parking lots, recreation facilities, and vacant lots. All built environment measures are proportions of block faces on and surrounding the census block which have that feature present. A proportion of one for abandoned buildings, for example, means that every block face on and around that block has at least one abandoned building. I exclude measures of commercial and residential security—such as bars on windows—which are protective measures undertaken by property owners that are likely to be endogenous to crime rates. My focus here is on community control of built environment features that provide opportunities rather than individual protective measures.

It is important to note that these features are likely spread across a continuum of perceived desirability by residents. Abandoned buildings have no positive functions for any neighborhood residents, with the possible exception of property owners awaiting rising values to redevelop or sell. In contrast, most commercial destinations and recreation facilities likely provide valuable amenities to the neighborhood. The degree to which collective efficacy is associated with the presence of these features is likely governed by the perceived balance of positive and negative impacts they make to the neighborhood. That is, even if a particular built environment feature—like a local park—is associated with crime, residents may not advocate for the removal of the property if it provides use value to the neighborhood that outweighs the cost of crime. In this way I diverge from studies which focus on the criminogenic effects and control only of “unpopular places” (Wilcox & Eck, 2011). It may be the case that many features are comparably criminogenic, but removal efforts are concentrated on those features perceived as particularly undesirable or unambiguously problematic.

For an analysis of the impact of past collective efficacy on the built environment, I construct a past collective efficacy measure from the 1995 PHDCN community survey (PHDCN-CS). I estimate this measure using the same multilevel approach as for the CCAHS. The PHDCN-CS is similar to the CCAHS’s community survey but produces more precise estimates of neighborhood social structures due to its larger sample size (N=8,782). The PHDCN SSO is not used for block-level analyses because it was conducted in only 80 neighborhood clusters and no block-level identifiers are available to link those blocks across surveys.

The neighborhood and block measures were linked to publicly-available geocoded Chicago Police Department crime data from the three years after the CCAHS (2004-2006) to obtain block-level counts of crime incidents (Chicago Police Department, 2020). A three-year span was used because serious crimes are relatively rare at the block level—using multiple years reduces the influence of idiosyncratic variation. I consider five forms of crime: (1) homicide, (2) assaults with a gun, (3) robbery, (4) any violent crime (defined as 1 through 3 plus assaults without a gun), and (5) any property crime (defined as burglary and theft). These forms of crime were chosen for two reasons. First, they are direct contact predatory violations likely to be particularly sensitive to different opportunities structured by the built environment. Second, accuracy of reporting tends to be higher for more serious crimes such as homicide and gun violence. These geocoded crime data are only publicly available from 2001 onward, which prevents constructing a complete block-level panel dataset even if the blocks in the 80 clusters of the PHDCN with built environment measures could be identified. The police records are also only geoidentified to the city block level, preventing the use of more granular geographic units sometimes used in the situational opportunity literature like properties and street segments (e.g., Sherman, Gartin, & Buerger, 1989; Weisburd, Groff, & Yang, 2012).

Lastly, census data from 2000 were used to adjust for block-level population density. Despite being collected in 2001-2003, CCAHS blocks were identified using 1990 census block boundaries to facilitate linking to the 1995 PHDCN. Consequently, 2000 block populations were areal weighted to the 1990 boundaries where boundaries changed across decennial censuses. Areal weighting is a process in which values describing one geographic area are assigned to another geographic area in proportion to the area of their intersection, under the assumption the values of interest are distributed uniformly in space. These resulting population values were then divided by block area to arrive at a block population density. This is a block-level analog of the tract-level normalization process for the LTDB which was used to construct neighborhood-level measures. The resulting final analytical data describe 1,641 blocks nested in 343 neighborhoods. Table 1 presents descriptive statistics for these data.

*Table 1 about here*

# Methods

I examine the relationships between collective efficacy, the built environment, and crime using a system of piecewise structural equations (see figure 3) which consist of (1) negative binomial mixed models of conditional direct associations of collective efficacy and built environment characteristics with crime and, (2) linear mixed models predicting present collective efficacy and built environment conditions using past collective efficacy. Piecewise structural equations are an alternative to conventional variance-covariance based structural equation models (SEM) which instead decompose the structural model into component regressions estimated separately (Shipley, 2016). This permits use of estimators which are unsupported in conventional SEM software or are computationally intractable. In the present case, a piecewise approach permits mixing single- and multi-level linear and negative binomial (gamma-poisson) models.

Because the component models are estimated individually, the fit of a piecewise system of equations is evaluated using tests of directed separation (d-separation) for each independence restriction in the system of models. In this case, the tests of direct separations are based on the significance of correlations between the residuals of endogenous variables and/or observed values of exogenous variables which the structural model implies should be zero (Shipley, 2016). These d-separation tests may then be summarized by a single Fisher’s C statistic which measures overall fit similar to chi-square tests based on comparisons of observed and predicted covariance matrices in conventional SEM. Both the Fisher’s C statistic and SEM chi-square may be described as simultaneous tests of the validity of all restrictions implied by the structural models.

*Figure 3 about here*

Figure 3 is a simplified version of the complete structural model. Each solid arrow represents a separate model or set of models testing the hypothesized causal pathway(s). The dashed arrow from past collective efficacy to crime is expected to be zero conditional on the included measures. This is evaluated using a test of d-separation for each outcome. The entire system of models was estimated together using the R package piecewiseSEM (Lefcheck, 2016; R Core Team, 2021).

All models—whether predicting crime or built environment conditions—adjust for prior (year 2000) neighborhood disadvantage, stability, and Hispanic/immigrant population. These models also adjust for neighborhood-level and block-level population density, rather than using a population offset to directly model rates as is often advised in models of crime counts (Osgood, 2000). This choice was made because it is unlikely block-level populations capture only the number of individuals at risk in a given block. Population density instead is likely to capture variation in all three key elements of criminal opportunity—likely offenders, suitable targets, and capable guardians—which is unaccounted for by the other structural covariates. Testing different functional forms of density revealed a strong quadratic relationship at the block-level in all models, which might be expected if density captures both potential targets and guardians: Crime is more likely to occur where there are sufficient people present to make targets abundant but not so many as to make it likely the crime will be observed or interrupted (e.g., St. Jean, 2007, p. 156). Inclusion of the density measures is also conservative, as removing them strengthens, rather than weakens the focal relationships.

While the models below take steps to address residual correlations—such as neighborhood random intercepts—I do not model spatial dependence between observations as is sometimes done in this literature (e.g., Morenoff, Sampson, & Raudenbush, 2001). This choice was made because the units of observation are from a sample of only 1,641 out of Chicago’s 20,000-some census-blocks. Most sampled blocks are not adjacent to another sampled block (see figure 2 above). This which prevents calculating adjacency-based spatial weights for spatial regression models or conducting tests of spatial dependence based on neighbor matrices (such as Moran’s I).

## Models of Crime

Hypothesis 1 proposes there is a conditional direct association between built environment features and specific types of crime based on the form of opportunities they provide—for instance, I expect commercial destinations to better predict robbery and property crime than homicide and gun assaults. While commercial destinations may promote crime of all kinds by bringing many people together, commercial destinations in particular feature suitable targets for theft (merchandise) and robbery (customers carrying cash). Figure 4 is a simplified diagram of the model focusing on the measures of interest. Note that the built environment box represents all eight built environment features—bars, liquor stores, vacant lots, abandoned buildings, commercial destinations, recreation facilities, parking lots, and mixed land use—and crime represents all five crime types—homicide, gun assaults, robbery, any violent crime, and any property crime. In all cases I expect a direct effect of collective efficacy on crime due to the mechanism of informal social control (and other forms of intervention). The dotted line indicates unmodeled pathways which are evaluated using tests of d-separation.

*Figure 4 about here*

I estimate the conditional direct effects of collective efficacy and the built environment on crime using negative binomial models with random intercepts for neighborhood clusters fit using R’s lme4 package (Bates, Mächler, Bolker, & Walker, 2015). Cluster intercepts address correlations in residuals for blocks in the same neighborhood. Conditional on the included covariates, the intra-class correlations are modest (between 0.10 and 0.20 depending on crime type), however BIC values and likelihood ratio tests indicate specifications with the random effects are at least weakly preferred except for homicide. In the case of homicide, the random effects do not improve model fit and cannot be stably estimated. Consequently, homicide is estimated with a conventional pooled negative binomial model which produces point estimates for the parameters of interest that are indistinguishable from those of the multilevel model.

## Models of the built environment and present collective efficacy

The next set of models estimate the conditional direct associations between past collective and the built environment, and between both past collective efficacy and the built environment and present collective efficacy. Hypothesis 2 posits that past collective efficacy influences the built environment, and hypothesis 3 posits that features of the built environment impact collective efficacy. The solid arrows in figure 5 depict the tested relationships.

*Figure 5 about here*

This part of the piecewise structural model consists of pooled and multilevel linear regressions. A pooled (neighborhood-level) linear regression was used to test the paths from the built environment and past collective efficacy to present collective efficacy. Multilevel (block-in-neighborhood) linear regressions test the paths from past collective efficacy to the built environment features. As before, all models adjust for neighborhood structural characteristics, and the built environment features are permitted to correlate with each other. Note that the neighborhood structural characteristics were measured in the year 2000 and past collective efficacy was measured in 1995. If collective efficacy influences any built environment features via these structural characteristics, this amounts to controlling for a post-treatment confounder (a mediator). Consequently, this may yield conservative estimates of the relationships between past collective efficacy and both the built environment and present collective efficacy. An alternative specification modeling these mediation pathways produced substantively equivalent results.

# Results

This section presents results from each set of models described above. The first subsection, Crime Results, provides estimates for the conditional direct associations of collective efficacy, the built environment, and tract- and block-level control with the five forms of police-reported crime. The second subsection, Built Environment and Collective Efficacy Results, contains estimates of the associations between past collective efficacy and the built environment, and the built environment and present collective efficacy.

## Crime Results

Figure 6 displays incidence rate ratios (IRR) for the conditional direct associations between the primary predictors of interest—collective efficacy and the built environment features—and crime. Each column represents a model for a different crime type. The displayed IRR is the estimated multiplicative difference in the count of crime incidents of a given type for a one standard deviation difference in the predictor. For example, a one standard deviation higher level of in abandoned buildings—21% more block faces with abandoned buildings on and around that block—is expected to be associated with, on average, about 20% more homicides and gun assaults than an otherwise similar block.

*Figure 6 about here*

The most notable result in figure 6 is the weak conditional direct association between collective efficacy and the five crime outcomes. Estimated IRRs for collective efficacy are between 0.91 and 0.94 across all outcomes except gun assault (0.99). Statistical significance of collective efficacy for the violence and property crime outcomes is a function of their higher frequency, and thus greater statistical power to detect effects, rather than of stronger relationships. These weak associations are not, however, the result of inclusion of the built environment features. Removing these features produces only slightly stronger estimates for collective efficacy. Overall, collective efficacy appears to have a modest relationship with crime in these data.

In contrast, the conditional direct associations of built environment features with crime are comparatively large as proposed in hypothesis 1. Homicide and gun assaults are significantly predicted only by abandoned buildings. All violent crimes, robbery, and property crimes are also associated with abandoned buildings, though less so. Features which provide targets of monetary value—commercial destinations, mixed land use, parking—are more strongly associated with robbery and property crime than homicide and gun assault. These features do, however, show similar associations with all violent crime. As noted before, this is consistent with routine activities theory if these built environment features are associated with increased foot traffic, which increases the potential for interpersonal interactions of any kind, including violent ones.

Against hypothesis 1, vacant lots, bars, and liquor stores show no significant relationship with crime. No features other than abandoned buildings exhibit a statistically significant association with homicide and gun violence—though both bars and mixed land use have estimates similar in magnitude to abandoned buildings. With regard to vacant lots, bars, and liquor stores, the absence of the expected associations may be due to treatment heterogeneity: The measures used do not distinguish between different types of establishments or vacant lots. It is possible, for example, that abandoned buildings are nearly always suitable for concealing weapons but only particular vacant lots are suitable—such as those with substantial debris or foliage. Similarly, it is likely certain bars provoke violence—due to service practices, property management, or clientele—while others do not, or even reduce it through monitoring and reporting of problems (Graham, Bernards, Osgood, & Wells, 2006). The present research design is unable to examine potential heterogeneity of this sort. The appendix examines the possibility that the effects of built environment features are moderated by collective efficacy—which might capture some heterogeneity—but I find little evidence for this.

For reference, the full model estimates, including controls, are found in table 2 below. These estimates are the log-count marginal effects on crime from one standard deviation differences in predictors. is Nagelkerke for homicide (single-level model) and marginal Trigamma for the other outcomes. That is, the value of 0.56 for the Disadvantage row in the Homicide column indicates a one standard deviation higher level of disadvantage is associated with a 0.56 higher log-count of homicides on a given block. The IRR estimates in figure 6 are exponentiated values of these same estimates. The non-significant d-separation test p-values at the bottom of the table also indicate no association was found between past collective efficacy and any of the crime outcomes net of included tract and block covariates (Overall Fisher’s , , ). This result is consistent with the expectation, shown as a dashed line in figure 3, that past collective efficacy exerts no protective effect on crime except via present collective efficacy or the built environment.

*Table 2 about here*

It is also noteworthy that property crimes display weak and negative relationships with disadvantage, unlike the other forms of crime which are positively related to disadvantage. This may be indicative of the availability or value of targets for property crime in more structurally advantaged areas, or perhaps due to differential rates of reporting across neighborhoods. Block-level population density also exhibits a strong parabolic relationship to crime in all models. Under the strong assumption block population density captures the average number of people in the area at any given time, this may be evidence for the aforementioned opportunity tradeoff between the number of available targets and capable guardians. It is likely some degree of the apparent criminogenic effects of built environment features—and, in particular, heterogeneity within categories of features—is due to higher flows of people (Wilcox & Eck, 2011). A more convincing test would require measures of the stocks or flows of people at the block level (see Browning, Pinchak, & Calder, 2021).

## Built environment and collective efficacy results

The next set of models test the second hypothesis—past collective efficacy reduces the presence of criminogenic features of the built environment—and the third hypothesis—criminogenic features of the built environment reduce collective efficacy. To test hypothesis 2, I estimate the conditional associations of the neighborhood structural characteristics and past collective efficacy with features of the built environment. To test hypothesis 3, I estimate conditional associations of neighborhood structure, past collective efficacy, and present built environment features with present neighborhood collective efficacy. Together, the models used to test hypothesis 2 and 3 form the first stage estimates of the larger structural model shown in figure 3. Table 3 depicts the estimates obtained from the piecewise structural equations. All coefficients are fully standardized to facilitate comparison—units of both predictors and outcomes are in standardized, so coefficients may be interpreted as expected standard deviation differences in the outcome (heading measure) given one standard deviation differences in the predictor (left margin measure). Standard errors in parentheses. Coefficients significant at are bolded. values are conventional for collective efficacy (single-level model) and marginal for all others.

*Table 3 about here*

We see here that present collective efficacy is mainly predicted by past collective efficacy, stability, and disadvantage. In partial support of hypothesis 2, collective efficacy appears to be one of the primary predictors of abandoned buildings, mixed land use, vacant lots, and possibly commercial destinations.[[3]](#footnote-32) These associations are notable as abandoned buildings are the strongest predictor of homicide and gun assault under consideration, and mixed land use and commercial destinations are important predictors of robbery, property crime, and general violence. In evidence against hypothesis 3, none of the built environment features appear to predict present collective efficacy net of the other covariates.

As noted earlier, it is unlikely the present modeling approach satisfies the sequential ignorability assumption necessary to identify the mediated causal effect of past collective efficacy on crime via the built environment (Imai, Keele, & Yamamoto, 2010). Estimates of these mediated pathways may still be of interest as descriptive results. If we assume the structural model is correctly specified, the estimated average reduction in block counts of crimes from a one standard deviation higher level of collective efficacy (based on the IRR) is 2.0% for property crime and between 3.5% and 3.7% for all other types. For homicide, nearly all of the protective indirect association (3.7%) is attributable to reductions in abandoned buildings (2.0 percentage points) and mixed land use (1.4 percentage points). These indirect associations appear relatively modest, but are substantial when compared to the estimated direct associations between collective efficacy and crime. The indirect associations for homicide, robbery, violent crime, and property crime range from one third and to one half the magnitude of the direct collective efficacy associations. For gun assaults, the indirect association with past collective efficacy (-0.037) is over three times the estimated direct association with present collective efficacy (-0.011).

# Discussion

The first primary finding in this work is that, in contrast to expectations from the theoretical framework, the direct association between present collective efficacy and crime is small in magnitude conditional on block-level covariates and structural neighborhood characteristics. Past research using similar research designs typically finds a much stronger negative relationship of collective efficacy on crime (Lanfear, Matsueda, & Beach, 2020), including one analysis using the same CCAHS data, though pooled with the 1995 PHDCN data and aggregated to tracts instead of larger neighborhood clusters (Sampson, 2012, pp. 173–177). The weak effects found here do not appear to be the result of underpowered tests as the associations between crime and collective efficacy are estimated relatively precisely. Similarly, it does not appear to be due to spuriousness from the built environment features, as removing them from the model does not notably strengthen the estimates. It is possible the modest effect of collective efficacy is in part attributable to the smaller sample size in the 2003 survey (3,105), as compared to the 1995 survey (8,782), which yields less reliable estimates of neighborhood collective efficacy (0.50 vs. 0.76). The lower average reliability in 2003 may translate into reduced overall variation in collective efficacy and thus reduced statistical power to detect its effects on crime.

As expected theoretically, criminogenic built environment features appear to be related to past collective efficacy, suggesting collective action might affect crime by altering the physical environment. Abandoned buildings and mixed land use appear particularly important. If these results are robust, the existence of a collective efficacy crime control pathway via the built environment is important because changes to the environment don’t require continued intervention, thus making them stable and low cost to residents (MacDonald, Branas, & Stokes, 2019). By reducing neighborhood problems, this may even augment informal social control—or reinforce it over time, indirectly, via the established negative effect of crime on collective efficacy (Sampson, 2012). Future research should attempt to replicate this result in other settings, as well as investigate the proposed mechanism—influence over local government agencies and policymakers—which could not be examined with the present research design.

No evidence was found, however, for a direct influence of these built environment features on collective efficacy net of neighborhood structural measures. It is possible, however, that collective efficacy is responsive to changes in the built environment features rather than levels. For example, perhaps resident confidence in their ability to solve problems is bolstered by declines in abandoned buildings and other problem properties, regardless of the overall number. Conversely, even at low levels of abandoned buildings, an increase of one or two abandoned buildings might be interpreted as a sign the neighborhood is in decline and out of control (Wilson & Kelling, 1982). This cannot be tested with the present data but should be considered in future research.

This relationship between collective efficacy and the built environment may have also implications for the stratification of neighborhoods within a metro area. The literature on the political economy of place and public social control tells us that differences in the ability to regulate the built environment contributes to race and class stratification (Logan & Molotch, 2007). For example, researchers have found collective action by affluent white neighborhoods, mainly via local government, helps maintain housing segregation and concentrate public housing in poor neighborhoods (Einstein, Glick, & Palmer, 2020). The ability of one neighborhood to exert control over its space can thus produce metro-wide consequences. This may foster the concentration of disadvantage, and thus crime, implicating collective efficacy in the process.

While this work focused on crime as an outcome, the reach of collective efficacy suggests a wider vision for the built environment as a mechanism. Collective efficacy is envisioned—and demonstrated—as a general problem-solving capacity associated broadly with community wellbeing (see Sampson, 2012, pp. 159–161 for a review). While I demonstrate negative associations between past collective efficacy and some criminogenic features likely perceived as problematic by residents—in particular abandoned buildings—it is reasonable to expect an opposite effect for features of the built environment that promote wellbeing. For example, highly collective efficacious neighborhoods may, as the indicator suggests, be more effective at preserving a library or fire station threatened by budget cuts. In this way collective efficacy may generally foster the development, maintenance, and improvement of built environment features that produce use value in neighborhoods (Logan & Molotch, 2007). This could not be tested with the present data, but it is an important avenue for future research.

The converse of this, of course, is that low collective may result in disadvantaged neighborhoods accumulating problematic features and losing beneficial ones. This includes public infrastructure as well. When governmental and institutional disinvestment occurs, the effects are more likely to be concentrated in neighborhoods unable to mount effective campaigns to maintain services. This may be particularly painful when communities face closures of beneficial local facilities and services, yet receive stable or even increasing levels of law enforcement scrutiny (Beck & Goldstein, 2018). Interventions in the built environment are a promising alternative to increased policing for addressing crime in disadvantaged neighborhoods, particularly serious violence (Kondo, Andreyeva, South, MacDonald, & Branas, 2018). Remediation of criminogenic features of the environment is often inexpensive, effective, and politically feasible—and generates benefits beyond crime control (MacDonald, Branas, & Stokes, 2019). For example, Branas et al. (2018) found vacant lot remediations increased resident outdoor socializing and reduced fear of victimization. Substantial reductions to crime and improvements to wellbeing could be made in disadvantaged neighborhoods using programs that work with communities to address problematic built environment features—and create or improve beneficial ones.

While these results are suggestive, this approach does not conclusively establish a causal relationship nor provide evidence for the proposed mechanism of influencing local government and other institutions governing property development. Ideally, stronger tests of these relationships and mechanisms would be conducted using longitudinal designs and field experiments. This is, however, a challenging target for quantitative research due to the combination of slow change in the built environment and the interdependence of social and physical characteristics of neighborhoods. These relationships and mechanisms may be more amenable to qualitative or mixed-method approaches examining collective action to alter the built environment for crime control purposes. This might include observation of public meetings—such as of zoning boards—as well as analysis of meeting records and media reports of protests, legal actions, and direct interventions. Analyses linking rich qualitative data to existing quantitative data on neighborhood collective efficacy, the built environment, and crime are likely to be illuminating in this area.

Another limitation of these analyses is that they cannot strongly test the potential moderating effects of neighborhood context on the associations between built environment characteristics and crime (see Built Environment Moderation in the appendix). It is a common finding in the situational opportunity literature that local contextual features exhibit effects moderated by the social structure of the community (Wilcox, Land, & Hunt, 2003). For example, the impact of alcohol outlets on crime appears conditional on neighborhood social structures (Pridemore & Grubesic, 2012). In other cases, the strongest evidence for built environment effects comes from studies restricted to disadvantaged contexts. As an example, remediation experiments that found the strong effects of vacant lots on violent crime were conducted primarily in poor, high crime neighborhoods (Branas et al., 2018). These effects may be weaker in less disadvantaged contexts. Importantly, if certain features increase crime only under particular conditions, one would expect residents to work to remove them only under those same conditions, unless they are otherwise problematic (e.g., threatening property values). In the present study, there appears to be insufficient power to stably test interactions with collective efficacy or disadvantage. Stronger examinations of multilevel interactions are an obvious next step but require more statistical power than the present data permit, particularly given the rarity with which contexts like abandoned buildings are found in more advantaged neighborhoods.

In a related vein, more refined measures may be needed to accurately estimate relationships between built environment features and crime. It is possible that the weak relationship between vacant lots and crime and unstable estimates for alcohol outlets are due to heterogeneity in social meaning and function of these places, or differences in reporting behavior rather than underlying rates of crime. For alcohol outlets in particular, these results may reflect differences in management, with some particularly well-regulated and others not (Graham, Bernards, Osgood, & Wells, 2006). More broadly, efficacious place management is a major source of heterogeneity of criminogenic effects between otherwise similar places (Eck & Madensen, 2018). Due to coarseness of measures, this analysis treats all built environment elements of a given type as equivalent. For example, this analysis treats bars that engage in over-service and turn a blind eye to illicit activity as equivalent to well-regulated ones, and it treats all vacant lots as similar, while their true effect is likely contingent on the concealment they provide. Similarly, due to an absence of measures of street occupancy, this analysis treats busy blocks and properties as equivalent to low-traffic ones, which is important given foot traffic is likely correlated with the presence of different built environment features (Wilcox & Eck, 2011).

This calls for better measures. Future research might, for example, distinguish between different types of alcohol outlets using business descriptions or administrative records like liquor violations, or capture local foot traffic using human mobility data (Browning, Pinchak, & Calder, 2021). Similar tests of heterogeneity should be pursued for all built environment characteristics. Some portion of this heterogeneity may also be captured using the moderation models proposed above if the unobserved characteristics of properties are related to overall neighborhood context (e.g., Pridemore & Grubesic, 2012). Future work should consider both moderation by neighborhood context and effect heterogeneity in the built environment. An ideal research design would also feature independent data collection for crime and victimization at small geographic areas to address unobserved heterogeneity in reporting of crime to police. Ideally, these data would capture built environment measures in multiple time points to test whether change in built environment features is more consequential than prevalence.

Different forms of social capital—such as reciprocated exchange or intergenerational closure—may also be more relevant than social cohesion or control expectations for the task of controlling the built environment. Similarly, it is likely that resources such as legal expertise—which may be inconsequential for informal social control—are important predictors of collective efficacy for these tasks (e.g. Einstein, Glick, & Palmer, 2020). This might be addressed in future surveys on collective efficacy by including questions about the perceived capacity of neighborhood residents to engage in legal or political challenges.

Finally, making changes to the built environment often requires working through institutions that may be unresponsive or even hostile—particularly to neighborhoods which are disadvantaged or have large BIPOC populations. It is important to account for this when estimating collective efficacy for tasks that require operating through such institutions. Future work would benefit from constructing task-specific collective efficacy measures for working with local government. These measures would ideally capture resident expectations for the responsiveness of actors, such as public officials. This responsiveness may also differ strongly by metropolitan context. For example, Chicago, the city under study, may be a unique context for citizen-government interactions. On the one hand, the city may be more responsive to collective action of residents due to its decentralized system of governance, in which each of the city’s 50 wards elects an alderman to the city’s legislative body. Residents frequently work through these aldermen or their appointees to influence city government to address crime (e.g., Carr, 2005; Vargas, 2016). On the other hand, this system of government is also characterized by political competition that may inhibit the ability of neighborhoods to fight serious crime (Vargas, 2016). In other cities, policymakers may be more or less responsive to the demands of residents—or the demands of developers and owners of properties residents perceive as problematic. Criminogenic effects resulting from poor guardianship by property owners may be particularly elevated where owners feel little pressure from a city government unresponsive to residents (Eck & Madensen, 2018). Data from other cities, or, better, from a multi-city sample, should be used to examine whether this study’s findings are replicable in different contexts of local government.

Despite these limitations and outstanding questions, I believe this analysis makes an important contribution to the literature on neighborhood crime control. The theoretical framework presented suggests a new mechanism by which collective efficacy may shape neighborhood crime rates—control of the built environment. All included features of the built environment were associated with some form of crime. Most prominent, however, were abandoned buildings which are strongly associated with serious violence. Abandoned buildings, in turn, were strongly negatively associated with past collective efficacy. This may be the result of a process in which collective efficacy facilitates removal of abandoned buildings, which in turn results in reduced violence. Similar results were found for mixed land use, which is primarily associated with property crime. No support was found for the hypothesis that criminogenic features of the built environment reduce neighborhood collective efficacy.

These results provide support for a broader collective efficacy model of neighborhood crime control which incorporates control of the built environment. Despite often being used to operationalize only informal social control, collective efficacy has been conceived of as a general problem-solving capacity of neighborhood residents (Lanfear, Matsueda, & Beach, 2020; Sampson, 2012). Situational opportunity theories of crime have highlighted the importance of features of the built environment in facilitating crime. The framework used here links the neighborhood-level theory of collective efficacy with situational opportunity by proposing that collective efficacy may facilitate the removal of criminogenic features of the built environment. Rather than just promoting guardianship by residents, such as monitoring or direct intervention, collective efficacy may also reduce crime by empowering residents to remove or prevent the development of sources of criminal opportunities. This crime control pathway is important because changes to the built environment are long-lasting and reduce the need for future resident interventions against crime. Control of the built environment has implications beyond crime as well, as the built environment is a major factor governing the quality of life and wellbeing of residents (Logan & Molotch, 2007; MacDonald, Branas, & Stokes, 2019). This may be an important mechanism by which collective efficacy promotes stable, safe, and livable neighborhoods.

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TABLE Descriptive statistics

|  | Measure | Mean | SD | Min | Density | Max |
| --- | --- | --- | --- | --- | --- | --- |
| Neighborhood (N=343) | | | | | | |
|  | Collective Efficacy (2003) | 0.00 | 1.00 | -3.64 |  | 2.81 |
|  | Collective Efficacy (1995) | 0.00 | 1.00 | -2.93 |  | 3.00 |
|  | Disadvantage | 0.00 | 1.00 | -2.35 |  | 3.45 |
|  | Stability | 0.00 | 1.00 | -2.39 |  | 2.04 |
|  | Hispanic/Immigrant | 0.00 | 1.00 | -1.60 |  | 2.30 |
|  | Density (Neighborhood) | 7.09 | 4.37 | 0.18 |  | 31.61 |
| Block (N=1,641) | | | | | | |
|  | Homicide | 0.10 | 0.35 | 0.00 |  | 4.00 |
|  | Gun Assault | 0.98 | 1.69 | 0.00 |  | 18.00 |
|  | Robbery | 3.18 | 4.39 | 0.00 |  | 44.00 |
|  | Violent | 6.58 | 8.57 | 0.00 |  | 85.00 |
|  | Property | 20.33 | 24.62 | 0.00 |  | 315.00 |
|  | Abandoned | 0.12 | 0.21 | 0.00 |  | 1.00 |
|  | Bars | 0.05 | 0.13 | 0.00 |  | 1.00 |
|  | Commercial Dest. | 0.21 | 0.26 | 0.00 |  | 1.00 |
|  | Liquor | 0.03 | 0.10 | 0.00 |  | 0.75 |
|  | Mixed Use | 0.32 | 0.32 | 0.00 |  | 1.00 |
|  | Parking | 0.11 | 0.16 | 0.00 |  | 1.00 |
|  | Recreation | 0.05 | 0.09 | 0.00 |  | 1.00 |
|  | Vacant | 0.12 | 0.21 | 0.00 |  | 1.00 |
|  | Density (Block) | 10.85 | 7.59 | 0.00 |  | 83.42 |

TABLE Negative binomial estimates of crime

|  | Predictor | Homicide | Gun Assault | Robbery | Violent | Property |
| --- | --- | --- | --- | --- | --- | --- |
| *Neighborhood* | | | | | | |
|  | Coll. Eff (2001) | -0.10 (0.10) | -0.01 (0.05) | -0.07 (0.04) | **-0.09 (0.04)** | **-0.07 (0.03)** |
|  | Disadvantage | **0.56 (0.11)** | **0.70 (0.06)** | **0.22 (0.04)** | **0.39 (0.04)** | **-0.08 (0.03)** |
|  | Stability | -0.04 (0.13) | -0.02 (0.06) | **0.16 (0.05)** | **0.14 (0.04)** | **0.30 (0.03)** |
|  | Hispanic / Immigrant | **-0.36 (0.11)** | **-0.16 (0.05)** | **-0.41 (0.04)** | **-0.33 (0.04)** | **-0.23 (0.03)** |
|  | Density (Neighb.) | **0.23 (0.11)** | 0.07 (0.06) | **0.25 (0.05)** | **0.16 (0.04)** | **0.09 (0.03)** |
| *Block* | | | | | | |
|  | Abandoned | **0.19 (0.07)** | **0.18 (0.04)** | **0.09 (0.03)** | **0.13 (0.03)** | **0.05 (0.02)** |
|  | Bars | 0.16 (0.10) | 0.03 (0.04) | -0.05 (0.03) | -0.01 (0.03) | -0.01 (0.02) |
|  | Commercial Dest. | -0.17 (0.15) | 0.04 (0.06) | **0.24 (0.04)** | **0.19 (0.04)** | **0.11 (0.03)** |
|  | Liquor Stores | -0.02 (0.09) | 0.03 (0.04) | 0.03 (0.03) | 0.03 (0.03) | 0.00 (0.02) |
|  | Mixed Use | 0.16 (0.13) | 0.11 (0.06) | **0.15 (0.04)** | **0.10 (0.04)** | **0.09 (0.03)** |
|  | Parking | 0.12 (0.09) | 0.05 (0.04) | **0.07 (0.03)** | **0.08 (0.03)** | **0.09 (0.02)** |
|  | Recreation | 0.00 (0.08) | 0.04 (0.04) | **0.08 (0.03)** | **0.08 (0.02)** | 0.03 (0.02) |
|  | Vacant | 0.06 (0.08) | 0.04 (0.04) | 0.00 (0.03) | 0.01 (0.03) | -0.00 (0.02) |
|  | Density (Block) | 0.07 (0.16) | 0.12 (0.06) | **0.10 (0.04)** | **0.18 (0.03)** | **0.10 (0.03)** |
|  | Density (Block)2 | **-0.60 (0.21)** | **-0.35 (0.08)** | **-0.09 (0.03)** | **-0.13 (0.03)** | **-0.05 (0.02)** |
| Past Coll. Eff. d-Sep. P-value | | 0.48 | 0.23 | 0.92 | 0.13 | 0.52 |
| R2 | | 0.14 | 0.17 | 0.28 | 0.36 | 0.29 |
| N = 1641 for all models | | | | | | |
| Standard errors in parentheses; Bolded estimates significant at 95% level | | | | | | |

TABLE Linear model estimates of built environment features and collective efficacy

|  | Predictor | Collec. Effic. | Aband- oned | Bars | Commer. Dest. | Liquor Stores | Mixed Land Use | Parking | Recre- ation | Vacant |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| *Neighborhood* | | | | | | | | | | |
|  | Coll. Eff. (1995) | **0.24 (0.03)** | **-0.11 (0.04)** | -0.04 (0.04) | -0.07 (0.04) | -0.02 (0.04) | **-0.09 (0.04)** | -0.01 (0.04) | 0.03 (0.04) | **-0.14 (0.05)** |
|  | Disadv. | **-0.14 (0.03)** | **0.32 (0.03)** | **-0.18 (0.03)** | **-0.12 (0.03)** | -0.01 (0.03) | **-0.12 (0.03)** | -0.06 (0.04) | -0.06 (0.04) | 0.00 (0.04) |
|  | Stability | **-0.20 (0.03)** | 0.01 (0.04) | **0.12 (0.03)** | **0.19 (0.03)** | **0.13 (0.03)** | **0.21 (0.04)** | **0.25 (0.04)** | **0.25 (0.04)** | 0.08 (0.04) |
|  | Hispanic / Immigrant | 0.04 (0.02) | **-0.18 (0.03)** | **0.17 (0.03)** | **0.16 (0.03)** | -0.01 (0.03) | **0.21 (0.03)** | -0.04 (0.03) | -0.06 (0.03) | 0.07 (0.04) |
|  | Density (Neighb.) | **-0.07 (0.03)** | -0.02 (0.04) | -0.04 (0.03) | -0.02 (0.04) | 0.03 (0.04) | -0.03 (0.04) | 0.06 (0.04) | -0.05 (0.04) | -0.07 (0.05) |
| *Block* | | | | | | | | | | |
|  | Abandoned | -0.05 (0.02) | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Bars | 0.02 (0.02) | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Commer. Dest. | -0.00 (0.04) | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Liquor Stores | 0.04 (0.02) | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Mixed Use | -0.05 (0.03) | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Parking | 0.04 (0.02) | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Recreation | -0.02 (0.02) | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Vacant | -0.02 (0.02) | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Density (Block) | **-0.09 (0.03)** | -0.04 (0.03) | -0.03 (0.03) | 0.04 (0.03) | -0.01 (0.03) | 0.04 (0.03) | **-0.07 (0.03)** | -0.00 (0.03) | -0.01 (0.03) |
|  | Density (Block)2 | 0.01 (0.02) | 0.01 (0.02) | -0.00 (0.03) | -0.03 (0.03) | -0.01 (0.03) | 0.02 (0.02) | **0.07 (0.03)** | 0.00 (0.03) | -0.02 (0.02) |
| R2 | | 0.3 | 0.22 | 0.07 | 0.11 | 0.02 | 0.13 | 0.06 | 0.05 | 0.03 |
| N = 1641 for all models | | | | | | | | | | |
| Standard errors in parentheses; Bolded estimates significant at 95% level | | | | | | | | | | |

1. Two neighborhoods are unusually large at over 10 square miles each, due to the inclusion of large open areas: O’Hare Airport and Lake Calumet. [↑](#footnote-ref-25)
2. I calculated 1990 factor scores without this same indicator and compared them to those calculated by Sampson, Raudenbush, and Earls (1997). All three factors exhibit correlations greater than .95 with equivalents from Sampson, Raudenbush, and Earls (1997). [↑](#footnote-ref-26)
3. I note the result for commercial destinations because the estimate is large in magnitude but its similarly large standard error is due to variance inflation from a high correlation with mixed land use (0.75). Similar, but more precise, results are obtained for both predictors by omitting the other. They were not combined into a composite measure because a test of linear equality restrictions was rejected. [↑](#footnote-ref-32)