Integrating Collective Efficacy and Criminal Opportunity: Disorder, the Built Environment, and Policing

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Abstract

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This dissertation proposes an integrative theory that links social structural explanations of neighborhood crime to opportunity-based situational explanations for crime. The first chapter of this dissertation argues that the neighborhood-level theories of collective efficacy and broken windows may be unified into a multilevel theory of situations using Cohen and Felson's (1979) routine activities theory and a pragmatist model of roles and perception. I discuss empirical implications of this integrated theory. The second chapter proposes that collective efficacy inhibits crime in part by permitting neighborhoods to remove and prevent built environment features that generate criminal opportunities. I find evidence collective efficacy is negatively related to the presence of abandoned buildings and mixed land use which, in turn, promote crime. The third chapter interrogates the role of police efficacy—resident perceptions of police effectiveness and legitimacy—in collective efficacy theory. In contrary to established research in this area, I find evidence that collective efficacy causally precedes police efficacy. In the conclusion I discuss implications for future research and advocate for situating collective efficacy in a multi-level crime, opportunity, and political economy framework.

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DEDICATION

For my mom and dad

INTRODUCTION

This dissertation proposes an integrative theory that links social structural explanations of neighborhood crime—collective efficacy (Sampson 2012) and broken windows (Wilson and Kelling 1982)—to opportunity-based situational explanations for crime. I do this using the language of routine activities theory, which describes predatory crime as the result of the convergence in time and space of individuals occupying three abstract roles: likely offenders, capable guardians, and suitable targets (Cohen and Felson 1979). My framework explains how the social structural characteristics and physical environment of neighborhoods are related to the distribution of actors taking these roles in space and time. I also consider how individuals and groups work to alter these distributions and their determinants, and how the resolutions of situations may lead to changes in the social structure and physical environment of neighborhoods.

I develop this multilevel theoretical framework of neighborhood social structure and situational crime in my first chapter, "A Situational Explanation of Neighborhood Crime." I then apply elements of this framework to examine two pathways of neighborhood crime control in my empirical chapters. The first focuses on how neighborhoods may alter the built environment to constrain criminal opportunities. The second focuses on how neighborhood collective efficacy relates to the perceived effectiveness and legitimacy of police, and in turn, how both relate to rates of crime.

0.1 A Situational Explanation of Neighborhood Crime

The first chapter of this dissertation argues that the neighborhood-level theories of collective efficacy and broken windows may be unified into a multilevel theory of situations using Cohen and Felson's (1979) routine activities theory and a pragmatist model of roles and perception. I first describe collective efficacy and broken windows theories in terms of their causal mechanisms. While both theories operate at the macro-level, they rely on individual perceptions as mediating micro-level mechanisms. I then introduce routine activities theory, which describes crime as the result of convergences of individuals fitting abstract crime-relevant roles. These convergences are a particular configuration of a situation. Using the pragmatist symbolic interactionist theory of Mead (1934), I elaborate on the relationship between roles, perception, and situations of crime. With the situation as a foundation, I construct a multi-level theory that integrates collective efficacy, broken windows, and criminal opportunity.

This theory focuses on crime as a situational phenomenon, resulting from interactions between actors and objects in places. The meanings actors attribute to situations—including to themselves vis-à-vis the situation—determine how they behave in those situations. The initial meanings of situations are partly the result of past experiences of actors and partly the result of shared meanings to which the actors have been exposed. These meanings are also jointly constructed by actors within the situation via communication, giving situations emergent properties. The manner in which a situation resolves shapes how the involved actors interpret similar situations in the future. These meanings may in turn be communicated to others, contributing to shared meanings within collectivities like neighborhoods. In this way, macro-level shared meanings both impact behavior in situations, partly determining how they are resolved, and are created and propagated by situations.

0.2 Collective Efficacy and the Built Environment

The second chapter of this dissertation proposes that collective efficacy empowers neighborhoods to remove and prevent built environment features that generate criminal opportunities. Just as crime is concentrated in particular neighborhoods, within neighborhoods crime is concentrated in particular criminogenic locations (Weisburd, Groff, and Yang 2012). Research suggests criminogenic locations are largely determined by characteristics of the built environment (St. Jean 2007; Wilcox and Cullen 2018). Neighborhoods may seek to control crime by removing criminogenic locations and preventing development of properties that are perceived to present criminal opportunities.

This chapter empirically tests the relationship between collective efficacy and the distribution of potentially criminogenic features of the built environment, and the associations between those features and incidents of police-reported crime. I accomplish this using 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, in particular abandoned buildings.

0.3 Collective Efficacy and Formal Social Control

The third and final chapter of the dissertation interrogates the role of resident perceptions of police effectiveness and legitimacy in collective efficacy theory. Some authors describe collective efficacy as in part the result of perceptions of legitimate, effective, and responsive policing—police efficacy. When police efficacy is high, it promotes collective efficacy resulting in residents being more likely to engage in acts of informal social control (Drakulich and Crutchfield 2013; Silver and Miller 2004). Sampson (2012; Sampson, Raudenbush, and Earls 1997), however, describes collective efficacy as the ultimate source for all forms of neighborhood social control, including both informal control actions by residents and calls to police for formal control actions. This suggests efficacious policing is promoted by collective efficacy rather than vice versa.

This chapter attempts to adjudicate between these two causal orders by answering the question, does efficacious policing foster collective efficacy, or does efficacious policing depend on the collective efficacy of the community? Based on my theoretical framework, I also examine the possibility that collective efficacy and police efficacy moderate one-another, exhibiting a multiplicative protective effect on crime. I test these propositions using data from 1995 and 2003 in an array of panel models that make different assumptions about causal relationships, unobserved variables, and temporal and spatial dependence. My primary finding is that police efficacy appears to be descended from collective efficacy, rather than vice versa. I propose this occurs because effective and legitimate policing is reliant on residents' shared norms and willingness to intervene against crime and deviance. I also find weak evidence for the moderation hypothesis. Lastly, effects of both collective efficacy and police efficacy on crime appear modest, and stronger in 1995 than in 2003.

Chapter 1

A SITUATIONAL THEORY OF NEIGHBORHOOD CRIME

1.1 Introduction

This chapter proposes an integrative theory that links social structural explanations of neighborhood crime—collective efficacy and broken windows—to opportunity-based explanations for crime—routine activities. This first chapter serves two purposes: In the first half, I present a comprehensive overview of the key theories used in this dissertation, and, in the second half, I propose a situational micro-foundation based on social interaction that links these theories into a multilevel criminal opportunity framework.

The first half begins by describing collective efficacy and broken windows theories in terms of their causal mechanisms. While both theories operate at the macro-level, they rely on individual perceptions as mediating micro-level mechanisms. Neither, however, features a fully-articulated theory of individuals or the situations in which crime occurs. I then introduce routine activities theory, which describes crime as the result of convergences of individuals and objects fitting abstract crime-relevant roles. This language is useful for connecting collective efficacy and broken windows and introducing aspects of criminal opportunity neglected by collective efficacy and broken windows. While a powerful tool for analyzing macro-level variation in crime, routine activities also features an incomplete theory of individuals and the situation which limits its utility for analyses at smaller scales. I argue that linking these social structural theories together provides a more complete theory of neighborhood crime, but doing so requires a fully-articulated micro-theory of the situation.

In the second half of the chapter, I use a pragmatist micro-theory to elaborate a situational foundation for these theories based on roles and perception (Matsueda and Lanfear 2021). This situational foundation links collective efficacy, broken windows, and routine activities into a framework that explains how the social structural characteristics and physical environment of neighborhoods are related to the distribution of roles in space and time. I also consider how individuals and groups work to alter these distributions and their determinants, and how the outcomes of situations contribute to changes in social structure and the physical environment by altering shared meanings. While the social structural theories under consideration presently have unarticulated or incomplete micro-level mechanisms, this situational explanation provides explicit social mechanisms compatible with their core claims and existing empirical evidence. I conclude with empirical implications for studies of neighborhood crime.

1.2 Collective Efficacy

Collective efficacy is conceptualized as a neighborhood capacity for achieving a common goal—typically one which cannot be accomplished without collective action (Sampson, Raudenbush, and Earls 1997). Intellectually rooted in social disorganization theory, Sampson and colleagues' collective efficacy theory posits that a major source of neighborhood variation in crime rates is the differential capacity of neighborhoods to produce social control (Sampson, Raudenbush, and Earls 1997). Following Janowitz (1975), they define social control as the capacity of a group to regulate its members' behavior to realize collective goals, such as maintaining a safe environment.[1] For the purpose of controlling crime and disorder, collective efficacy represents a process through which latent social capital resources—such as norms, trust, and cohesion—are translated into action—resident interventions against deviance.

Sampson (2012:182) describes collective efficacy as an emergent property of neighborhood social structure, rather than the simple aggregation of the abilities of members to accomplish the task in question. It is characterized by an arrangement of social capital which facilitates collective goal-oriented actions. Specifically, collective efficacy for the task of social control

[1] Collective efficacy theory assumes consensus in normative goals (living in an area free of crime), but variation in regulatory capacity (social control). This echoes the value assumptions of social disorganization reformulations based on control theory (Bursik and Grasmick 1993; Kornhauser 1978).

consists of an additive combination of perceived trust and cohesion combined with expectations that neighbors will engage in acts of informal social control, such as surveillance or sanctioning. This is based on claim that "the collective willingness to intervene in the neighborhood is enhanced under conditions of mutual trust and cohesion," (Sampson and Raudenbush 1999:620). This suggests, however, that trust and cohesion may either precede expectations for intervention or moderate their relationship with crime rather than exhibit an additive relationship as is commonly specified (Hipp 2016).

While collective efficacy is most often examined in the context of crime, in particular violence, collective efficacy is conceived of as a general capacity for achieving community goals through collective action (Sampson 2012; Sampson, Raudenbush, and Earls 1997). Consequently, it has been used to explain a variety of outcomes at the neighborhood level—prosocial behavior, domestic violence, birth weight, asthma (Sampson 2012:160). This mirrors Shaw & McKay's ([1969] 1942) original social disorganization research which recognized urban social problems of many forms cluster together because they are the result of the same structural disadvantages. It is theorized that different forms of social capital facilitate different actions, and thus different indicators might be used to operationalize collective efficacy for other purposes (Wickes et al. 2013).

1.2.1 Sources of Collective Efficacy

Rooted in the social disorganization tradition, the sociodemographic structure of neighborhoods is assumed to be a fundamental source of collective efficacy. Concentrated disadvantage, residential instability, and, to a lesser degree, racial/ethnic heterogeneity and immigration inhibit collective efficacy by depriving the community of resources, disrupting social ties, and impeding the realization of common values (Sampson 2012; Sampson, Raudenbush, and Earls 1997).

Social network ties and local organizations have been suggested as the primary mediators between sociodemographic structure and collective efficacy. These are believed to operate by producing social capital or providing social structures which can be mobilized to facilitate social control (Sampson 2012:157–58). For example, collective efficacy appears to be promoted by density of intimate ties (Morenoff, Sampson, and Raudenbush 2001) and reciprocated exchange (Sampson and Raudenbush 1999). Complicating this story, however, is evidence that reciprocated exchange also moderates collective efficacy, attenuating its negative relationship with crime (Browning 2009). Collective efficacy is, however, primarily about the content of social relations (e.g. trust, norms) rather than the structure of networks (e.g. ties) (Sampson 2012:45). This stands in contrast with earlier social disorganization formulations which emphasized social structures of neighborhoods—institutions, organizations, and ties (Bursik and Grasmick 1993; Shaw and McKay [1969] 1942). Certain social structures and resources support (or inhibit) the development of collective efficacy, but they are not sufficient alone to prevent crime and no particular arrangement—such as a dense web of intimate ties—is assumed necessary to prevent crime. What is key is that the social structure can support cohesion and trust and expectations for social control.

Finally, collective efficacy also appears to be the result of a number of feedback processes. First, collective efficacy exhibits a reciprocal relationship with crime: it both suppresses and is suppressed by crime (Sampson 2012). The literature suggests this occurs over time within neighborhoods through two mechanisms. First, at the individual level, residents update their expectations for the social control behavior of their neighbors based on crime and disorder they observe (Hipp 2016; Matsueda and Drakulich 2016). Second, crime increases fear of crime and perceived likelihood of victimization. In response, residents constrain their social behavior to reduce the risk of victimization, which reduces social interaction and monitoring, resulting in weakened social control capacity (Bellair 2000; Liska and Warner 1991; Markowitz et al. 2001; Sampson and Raudenbush 1999). This feedback appears weaker than either the effect of collective efficacy on crime (Sampson 2012; Sampson and Raudenbush 1999).

Collective efficacy, both directly and via structural features, is also influenced by conditions in nearby neighborhoods and city-wide processes. Structural disadvantage and crime are highly concentrated in space (Peterson and Krivo 2010). Proximity to concentrations of disadvantage and crime causes spillovers to nearby neighborhood even with little local sources of crime. Similarly, high collective efficacy appears to exhibit spillover effects, reducing crime in nearby areas (Sampson 2012). Taken together, this means collective efficacy tends to concentrate in particular areas, spatially reproducing itself. Taken together, these feedback processes explain why collective efficacy manifests high stability over time: as a general problem-solving capacity, it combats destabilization of antecedents within the neighborhood or in nearby areas.

1.2.2 Mechanisms for Collective Efficacy

Sampson and colleagues suggest collective efficacy inhibits disorder and minor deviance through both external and internal mechanisms of informal social control (Sampson 2012; Sampson, Raudenbush, and Earls 1997). In the external mechanism, residents directly intervene against norm violations—such as by verbally sanctioning. In the internal mechanism, the deviant behavior of actors is inhibited by their internalization of local norms or through deterrence by increasing expectations that residents will directly sanction them. This combination of internal and external mechanisms is common to social disorganization models based on control theory (Bursik and Grasmick 1993; Kornhauser 1978). Collective efficacy is assumed to inhibit more serious crime through these mechanisms as well, but also through an indirect external mechanism in which the direct social control interventions of residents remove contexts that give rise to serious crime—such as unsupervised peer groups (Maimon and Browning 2010; Sampson, Raudenbush, and Earls 1997:918).

Collective efficacy is also assumed to predict reporting crimes to police (Sampson 2012:152; Sampson and Raudenbush 1999:612), though most research in this area deemphasizes this mechanism, does not use calling police as an indicator for the efficacy, and does not estimate efficacy's relationship to calling police. If collective efficacy predicts calls for police service, this may operate in a fashion analogous to the primary internal and external informal control mechanisms, but with police as the sanctioning actors invoked by residents—that is, a formal control mechanism. Chapter 3 of this dissertation examines this alternate formal social control pathway, arguing it should be separated from the informal control pathway.

Similarly, collective efficacy is assumed to predict efforts to influence local government, such as organizing a referendum to shut down a problematic bar or petitioning housing authorities demolish a house used as a drug venue (Sampson and Raudenbush 1999:612). This mechanism is captured by common indicators of collective efficacy, unlike for contacting police, by asking respondents how likely it would be for their neighbors to organize to protect a fire station (or library) threatened with closure (Earls et al. 1999; House et al. 2011). Chapter 2 of this dissertation examines the relationship between collective efficacy and differences in the built environment, proposing influence over local government as a mechanism.

Collective efficacy is thus theorized to promote resident actions of any kind which further the goal of reducing crime and disorder, whether intervening personally, calling police, complaining to public agencies, or organizing politically. In this way, as Sampson and Raudenbush (1999) note, collective efficacy evokes the systemic model of social control (Bursik and Grasmick 1993; Hunter 1985), by "recogniz[ing] the articulation among the private (family), parochial (neighborhood), and formal (public) orders but stresses the agency of residents in establishing these connections." That is, collective efficacy captures the capacity for neighborhoods to activate any mechanism of social control. This suggests that, rather than a "pure" theory of informal social control, collective efficacy is a general theory of collective action for social control. This perspective emphasizes conditions necessary for collective action over the form of action taken: a collective effort is required regardless of how social control is maintained.

This perspective deemphasizes, however, the systemic model of social control's emphasis on articulation between levels, despite empirical evidence of interactions between collective efficacy (focusing on informal control) and perceptions of police efficacy (formal control) Drakulich and Crutchfield (2013). Sampson (2012:167) has suggested that perhaps in contexts where police and government are corrupt or ineffective and interventions are particularly dangerous, collective efficacy may promote survival rather than control of crime and deviance . This further suggests an interaction between resident capacities for collective action and their institutional context, one which may be relevant not just outside the United States, but perhaps also in American neighborhoods where residents perceive police and local government as illegitimate or hostile.

Importantly, collective efficacy does not appear to reduce criminal motivation of residents, as self-reported offending by youth is unrelated to the level of collective efficacy in their neighborhood of residence (Sampson, Morenoff, and Raudenbush 2005). This suggests collective efficacy reduces offending by regulating behavior situationally—restraining crime by residents and non-residents alike, but only in the focal neighborhood—rather than by reducing stable motivation—which would presumably inhibit crime only by residents, but would do so wherever they travel. This is further supported by evidence that neighborhood collective efficacy is negatively related to offending behavior of non-resident robbery offenders (Bernasco and Block 2009) and crime-prone youth (Wikström et al. 2010). This implies a different role for collective efficacy than is suggested by Janowitz's (1975) definition of social control as the capacity to regulate group-member behavior. Collective efficacy appears to regulate both member and non-member (i.e. non-resident) behavior within the neighborhood, but does not regulate member behavior outside the neighborhood. This also sits in contrast to Shaw & McKay's ([1969] 1942) original social disorganization study in which they analyzed the spatial distribution of residences of juvenile delinquents—emphasizing the conditions that promote participation in delinquency—rather than the locations where delinquents commit crime. In this way, collective efficacy theory appears to speaks to where and how often offending occurs but not how individuals become involved in crime.

The diversity of proposed mechanisms for collective efficacy highlights their ad hoc and empirically-driven nature. Collective efficacy is typically presented as a macro-level theory, but crime is a situational phenomenon, the outcome of a situation. To explain their empirical findings, researchers speculate at cross-level and micro-level mechanisms that might plausibly link collective efficacy to criminal situations. These mechanisms are organized around no unifying micro-level theory, whether at the individual level or the situation level, and the mechanisms are typically not observed, tested, or used to make predictions—they make sense of empirical observations rather than explain them (Watts 2014). The present chapter undertakes the task of specifying a situational explanation for collective efficacy and other social structural theories of neighborhood crime, one which generates testable propositions. Before specifying this explanation, I summarize broken windows, a theory of neighborhood crime which articulates some micro-mechanisms and is often presented as a competing explanation for crime to collective efficacy (Lanfear, Matsueda, and Beach 2020).

1.3 Broken Windows

The broken windows model describes neighborhoods as a system in which crime, disorder, and social control are reciprocally related (Wilson and Kelling 1982). Disorder increases crime by signaling to potential offenders that the likelihood of residents intervening against them is low. Disorder also increases crime by signaling to residents that the neighborhood is unsafe, resulting in withdrawal from public spaces and subsequent reduction in social control capacity. Then, "Such an area is vulnerable to criminal invasion. Though it is not inevitable, it is more likely that here, rather than in places where people are confident they can regulate public behavior by informal controls…" (Wilson and Kelling 1982:3). If this reduced social control capacity results in large increases in crime, withdrawal from public spaces turns to departure from the neighborhood—except for "the poorest or those who are blocked by racial prejudice"—resulting in the concentration of disadvantage and collapse of social control.

Because of feedback loops in the model, sudden changes that overwhelm the social control capacity of a neighborhood can result in a cascade of rapidly increasing crime and disorder and decreasing social control. The presence of this threshold—which separates stable neighborhoods from those in a "spiral of decay," (Skogan 1990)—is an underappreciated feature of the broken windows model. Wilson and Kelling (1982) state most neighborhoods exist in an equilibrium state where disorder is managed by informal controls, and they have sufficient surplus informal control capacity to address sudden challenges as they arise. This is a negative or balancing feedback loop which maintains system stability. However, if disorder exceeds some threshold and overwhelms the neighborhood's informal control capacity, residents begin to withdraw from public spaces and informal control recedes. Once this occurs, the neighborhood enters a disequilibrium state as the feedback loop becomes positive or explosive. Social control capacity will fall and crime will rise, and withdrawal will escalate to outmigration. Absent a stabilizing exogenous intervention, the neighborhood eventually enters a new absorbing equilibrium, a collapsed state "where the situation is hopeless," (Wilson and Kelling 1982:8).

1.3.1 Sources of Informal Social Control in Broken Windows

Wilson and Kelling (1982) suggest the ability and willingness of residents to regulate public space is rooted in two proximate factors: (1) surveillance and sanctioning capability provided by the presence of residents in public places and (2) attachment to the neighborhood and a commensurate sense of responsibility for enforcing its norms. The first case is essentially Jacobs's (1992) "eyes on the street": informal control alone is sufficient to regulate an area when there are many potential monitors or, as Wilson & Kelling (1982:7) write, "the ratio of respectable to disreputable people" is high. In the second case, Wilson and Kelling (1982) state people more likely to intervene where they feel responsibility for the community, and feeling responsibility is rooted in the perception that one is a member of the community. This evokes the cohesion and trust component of collective efficacy.

Police—the focus of the original in *The Atlantic*—do not directly provide informal social control but serve a supportive role: "The essence of the police role in maintaining order is to reinforce the informal control mechanisms of the community itself," (Wilson and Kelling 1982:5). While most social control is exerted directly by residents, they may also turn to police to resolve situations, particularly when attempts at informal social control are rebuffed. Wilson and Kelling describe two elements of the policing role which enable to them to bolster informal control: their formal role and corresponding capacity for force. First, police officers occupy a formal role that obligates them to address problems they observe or have brought to their attention by residents. That is, their feeling of responsibility to act is imposed by their role rather than their affective attachment to the community, leading them to intervene even when residents will not. Second, sanctions by police carry a threat of force generally not available to residents. The threat of arrest or violence is not as easily ignored as verbal sanctions from residents. Because residents may invoke police—and the role of officer carries an obligation to act and a legal capacity to use force—their informal sanctions be reinforced by the implicit threat of escalation.

1.3.2 Mechanisms for Broken Windows

Informal social control is the primary mechanism which constrains crime and disorder, and it does so directly through the sanctioning of offenders and indirectly through the threat of sanctions–deterrence. The suggestion that police can support informal social control efforts suggests similar mechanisms are at work when police—rather than residents—are agents of social control. Further, it suggests the effect of sanctions or threats of sanctions from residents is in part dependent on the perception that residents can escalate to invoking police if their informal sanctions are rebuffed. Chapter 3 of this dissertation examines these relationships at the neighborhood level.

In contrast to collective efficacy, broken windows is explicitly a multilevel model with articulated micro-level and inter-level mechanisms. In the direct mechanism, disorder reduces the perceived risk of sanction for offending and thus increases the likelihood of offending. This occurs because potential offenders interpret the presence of disorder to signify residents are unable or unwilling to intervene to regulate public space—disorder represents an indicator of criminal opportunity. If residents will not intervene against disorder, they are unlikely to intervene against serious crime as well. From the perspective of the offender, this can be seen to represent a general deterrence mechanism: If others were not been sanctioned for their past behavior, I will not be sanctioned for my future behavior. This pathway is a multilevel mode: Pervasive disorder in the neighborhood (macro condition) reduces perceived risk of sanctions (macro-micro transition), resulting in increased offending (micro-mechanism), which increases the crime rate (micro-macro transition). Evidence connecting disorder to individual offender perceptions of sanction risk is weak (St. Jean 2007). Evidence is stronger that neighborhood disorder—particularly social disorder—is associated with crime rates net of social control capacity (Lanfear, Matsueda, and Beach 2020). Where mechanisms are considered, this research suggests disorder may operate through crime-specific opportunities presented by some forms of disorder, rather than general reductions in perceived sanction risk (Lanfear, Matsueda, and Beach 2020).

While not a primary focus of the theory, broken windows also includes a within-individual or within-group behavioral escalation mechanism. If children are rowdy and no one scolds them, their rowdiness will increase in response. If teenagers loiter and are not dispersed, it leads to fighting and accumulation of litter. If the signaling mechanism operates through a general deterrence mechanism, this is the corresponding specific deterrence mechanism: If I was not sanctioned for my past behavior, I will not be sanctioned for my future behavior. If we assume actors are approximately rational—as suggested by broken windows—and the perceived probability of sanction is positively related to the severity of the violation, then we would expect unchecked behavior to result in escalation due to updating of the perceived risk of sanctions. This is consistent with Bayesian updating in a rational choice model of offending (Matsueda, Kreager, and Huizinga 2006). This is also suggested in collective efficacy research as a mechanism by which resident interventions against minor crime and deviance translate into reductions in serious crime: control and removal of contexts which may escalate to violence, such as youth loitering on the street (Sampson 2012:918; Sampson, Raudenbush, and Earls 1997:152).

In the indirect mechanism, disorder produces fear which reduces attachment to the community and causes withdrawal from public spaces, reducing neighborhood social control capacity. This occurs because residents also interpret the presence of disorder as an inability to regulate public space, and thus an inability to prevent serious crime. Because residents want to avoid having disquieting encounters or being victimized—rather than to victimize others—this perceived lack of regulatory capacity translates into fear which constrains social behavior.[2] Note that in broken windows fear is not just about being a victim of serious crime like robbery but also about being confronted by unpredictable people (see also Innes 2004). Fear, here, is about the belief that public spaces are unregulated and a source of worrisome,

[2]Harcourt (2001:17) states broken windows implies different mechanisms for the "honest people" and the "disorderly people" in that disorder causes the "honest people" to withdraw or move out of the neighborhood and "disorderly people" to move into the neighborhood and commit crimes. This omits a key intervening mechanism based on meaning: in broken windows theory, everyone interprets widespread disorder to indicate social control is weak. What is different is not how disorder operates but how that meaning is translated into behavior by individuals. People behaving differently from the same stimuli does not necessarily indicate the stimuli is perceived differently, but rather may indicate different motivations. When not seeking to offend, a potential offender may also avoid places that appear unregulated to minimize their likelihood of victimization.

potentially dangerous, encounters. The constrained social behavior which results from fear may be seen as a self-protective behavior which reduces the risk of personal victimization at the cost of increasing the risk to others (Bellair 2000). In this way, reduced social control may be seen as an externality arising from individually rational behavior . Important also is that the threat posed by a given situation is conditioned by individuals' perceived vulnerability. An "obstreperous youth" may be perceived as a nuisance to an able-bodied adult man but a serious threat to an elderly one—physically vulnerable people are thus likely to be more sensitive to disorder as signals of danger (Innes 2004), and thus more likely to constrain their behavior (Wilson and Kelling 1982).

Both attachment and use of public spaces are influenced by this fear. Fearful residents avoid others and restrict their activity spaces to home, safe locations, and the safest available routes between these locations. This reduces informal surveillance capacity—eyes on the street (Jacobs 1992). The perception that the neighborhood is unregulated alienates residents as well, reducing attachment and thus the perceived responsibility to intervene even in the restricted areas they use—analogous to inhibiting expectations for social control in collective efficacy. This pathway represents another multi-level model: Pervasive disorder in the neighborhood (macro condition) produces fear in individuals (macro-micro transition), resulting in constrained behavior (micro-mechanism), which inhibits the collective capacity for social control (micro-macro transition). While not explicit in the original broken windows model, withdrawal likely also reduces informal social control by inhibiting formation and maintenance of social ties, and thus social capital, which foster community social control (Bursik and Grasmick 1993). Evidence for disorder reducing social control—including specifically via fear—is relatively strong (Lanfear, Matsueda, and Beach 2020; see O'Brien, Farrell, and Welsh 2019 for a counterpoint).

Importantly, the mechanisms in broken windows all operate through perception and interpretation. While rooted in objective conditions, the effects of disorder are mediated by people's perceptions of the neighborhood as a whole. Individuals may see particular places or situations as dangerous—like where young men congregate—but the mechanisms of detachment and withdrawal are described as the result of seeing the entire neighborhood as an alien and dangerous place. This raises the question of how individual disorderly contexts and encounters translate into perceptions of the neighborhood—and, importantly, how perceptions of the neighborhood alter interpretations of particular situations. It does not follow from broken windows that disorder in one part of an otherwise orderly neighborhood will trigger the mechanisms at work. Disorder must be sufficiently pervasive or conspicuous to alter how the entire neighborhood is perceived.

In a related vein, Wilson & Kelling (1982:3) invoke perceptions of neighborhood norms:

> Because of the nature of community life in the Bronx—its anonymity, the frequency with which cars are abandoned and things are stolen or broken, the past experience of "no one caring"—vandalism begins much more quickly than it does in staid Palo Alto, where people have come to believe that private possessions are cared for, and that mischievous behavior is costly.

This passage suggests norms and expectations for social control matter in restraining crime—as in collective efficacy—but residents infer these from evidence of norm violations (see St. Jean 2007). Empirical evidence supports this position (Hipp 2016; Matsueda and Drakulich 2016). This could be interpreted as a separate normative mechanism (e.g. Harcourt 2001) or another statement of general deterrence.

In contrast to collective efficacy, broken windows provides micro- and cross-level mechanisms linking social structural conditions to criminal situations. These mechanisms are based, however, on a relatively simple model of the actor that relies on uniform and unambiguous interpretations of disorder and other contexts. Evidence for these mechanisms is mixed (Lanfear, Matsueda, and Beach 2020). Broken windows (like collective efficacy) also neglects the role of other factors that influence criminal situations, such as variation in the availability of targets or the presence offenders. The next section describes routine activities theory, a macro-level theory which provides useful concepts and language for relating social structure to criminal situations.

1.4 Routine Activities Theory

Routine activities theory describes an abstract model in which predatory crime results from the confluence of three necessary elements: suitable targets, likely offenders, and the absence of capable guardians (Cohen and Felson 1979). Because all three elements must be present at the same time and in the same place for these crimes to occur, rates of such crimes will change whenever the joint distribution of these elements changes in society or a community. Rooted in Hawley's (1950) theory of human ecology, routine activity theory is a population-level theory focused on direct-contact predatory violations that feed on the legitimate routine activities of the general population. Direct-contact predatory violations are defined as individual criminal incidents, "involving direct physical contact between at least one offender and at least one person or object which that offender attempts to take or damage," (Cohen and Felson 1979). Mutually-culpable crimes like prostitution and drug sales or crimes without contact, like some financial crimes, lie outside its original purview, though later work has extended its reach (e.g. Clarke and Felson 2004).

The focus of this theory is on how spatiotemporal organization of routine human activities translates criminality—regardless of its underlying source—into criminal actions. Because the joint distribution of offenders, targets, and guardians is determined by the patterning of legitimate routine activities in people's lives—where and how they work, recreate, shop, etc.—it is possible for large changes in crime rates to occur without shifts in the motivation or number of likely offenders—such as when guardianship is impaired or targets are made more attractive. Simply put, provided the same potential offenders, more crime will occur when crime is easier to commit. For example, Cohen and Felson (1979) illustrated that increases in overnight and out-of-town travel (impaired guardianship) corresponded to similar increases in residential burglary, and reductions in the weight of consumer electronics (increased target attractiveness) corresponded to increases in electronics theft. These occurred despite little change in conventional structural causes of criminal motivation such as poverty. This sits in contrast with models like classic social disorganization that specify crime as the result of structural disadvantage and social breakdown. Changes in routine activities due to improvements in quality of life—such as increased leisure time and superior consumer goods—may increase crime as well.

1.5 Likely Offenders

In routine activity theory, a likely offender is defined as an individual with criminal inclinations and the capability—proficiency or tools—to carry out those inclinations. Using the ecological metaphor, likely offenders are treated as a distinct population that uses predatory means to gain sustenance from the environment. The source of criminal motivation or criminality—long the primary focus of criminology—is taken as given. In doing so, routine activity theory de-emphasizes offenders and focuses on the undertheorized elements: suitable targets and capable guardians. A key insight of routine activity theory is that a great deal of variation in crime can be explained without concern for the sources of criminality itself. This represents a theoretical separation of the criminal involvement or participation (criminality) from criminal events (crime), also a key element of the criminological rational choice perspective (Clarke and Felson 2004; Cornish and Clarke 1986). Empirical research using routine activity theory typically assumes the distribution of likely offenders is related to structural conditions such as socioeconomic disadvantage (Cohen and Felson 1979) or equivalent to population density by assumption of invariant motivation (Wilcox, Land, and Hunt 2003). Further, because routine activity theory is agnostic to the source of criminality—likely offenders—it may be explicitly integrated with most theories of criminality—whether individual level, such as control theory (Felson 1986) or rational choice (Clarke and Felson 2004), or macro-level, such as social disorganization (Wilcox, Land, and Hunt 2003).

1.6 Suitable Targets

In routine activity theory, a suitable target is a person or property with some spatial and temporal location and which may be subject to harm or removal. Targets differ by their material or symbolic value (including liquidity), their visibility to and ease of access for likely offenders, and their resistance to the crime in question (e.g. size, weight, defensive capability). For a likely offender intending to profit by theft, the most suitable targets are thus expensive, portable, easily resold objects left in the open. Note that elements of suitability may be in conflict: For a likely offender interested in obtaining status gains through violence, a more difficult—that is resistant or dangerous—target may be attractive as that difficulty is entangled with their symbolic value as a target (e.g., Anderson 1990). Operationalizing suitable targets (as well as the other elements) for expressive or mutually culpable crimes is thus challenging. Note also that potential victims (whether a target or owner of a target) may take evasive actions—which influence visibility, access, or resistance—to reduce the possibility of victimization, which may lead offenders to choose other targets.

1.6.1 Absence of Capable Guardians

The final necessary component of a predatory crime is the absence of a capable guardian. There are many potential guardians that might prevent an act, and they may accomplish this via either intentional (e.g. sanctioning, calling police, active surveillance) or unintentional activity (e.g. passive surveillance). In this way guardianship, "links seemingly unrelated social roles and relationships to the occurrence or absence of illegal acts," (Cohen and Felson 1979:590). Later elaborations of routine activities introduced handlers and managers as additional social control agents. These additions specify clearer roles for certain actors. Handlers are actors with intimate affective ties to potential offenders. Drawing on control theory, it is assumed that a potential offender will be restrained from committing an offense if doing so would jeopardize the affective tie (Hirschi [1969] 2002). Place managers are actors who, as a consequence of ownership or being an agent of the owners, have rights to regulate access to and behavior within a property. In this chapter, I use the term guardian to refer broadly to any actor occupying the role of a potential social control agent.

It can be difficult to a priori specify an individual as a guardian, unless they occupy a role with formal obligations regarding guardianship (e.g. police, security guards, retail employees). For crimes that target property—rather than individuals—it is at least unambiguous that the absence of any individuals, beyond a likely offender, constitutes absence of a capable guardian. Accordingly, the absence of capable guardians for burglary has been operationalized with aggregate time spent away from home (Cohen and Felson 1979). For crimes that target individuals, such as robbery, time spent away from home may also increase victimization, but likely through supply of suitable targets rather than reduced guardianship.

1.6.2 The Built Environment

The language of routine activities allows us to integrate a factor neglected in both collective efficacy and broken windows: the built environment. The built environment has long been recognized as a one of the most important predictors of crime Jeffery (1977) and is a key cause of heterogeneity in the distribution of criminal opportunities (St. Jean 2007). Just as crime is concentrated in particular neighborhoods, within neighborhoods crime is concentrated in particular criminogenic locations—hot spots (Sherman, Gartin, and Buerger 1989; Weisburd, Groff, and Yang 2012). The locations of hot spots are largely determined by characteristics of the built environment (St. Jean 2007; Wilcox and Cullen 2018). By structuring the routine activities of people, the built environment generates hot spots characterized by the repeated convergence in time and space of motivated offenders, suitable targets, and the absence of capable guardians (Brantingham and Brantingham 1981; Cohen and Felson 1979). Situational opportunity theories of crime—including routine activities—suggest that different built environment characteristics provide opportunities for different types of crime, governing not just where crime occurs but what crime occurs (Wilcox and Cullen 2018).

1.6.3 A Language for Integration

I argue that Cohen and Felson's (1979) routine activity theory provides a unifying language for linking collective efficacy to broken windows and the built environment. By using this language, we can see how the disparate theories fit together, and identify compatible and competing hypotheses among specific theories. From within this model, collective efficacy focuses on how neighborhoods increase guardianship by strengthening informal social control. Again within this model, broken windows posits that disorder signals to offenders an absence of capable guardians and inhibits guardianship by causing residents to withdraw from public spaces (Wilson and Kelling 1982). Finally, within this model, the built environment dictates the suitability of targets and affects guardianship by revealing or concealing criminal behavior (Wilcox and Cullen 2018).

This routine activities framework allows us to compare these theories. For example, it reveals that, beyond the mechanism of collective efficacy, communities can also control crime by keeping out likely offenders, hardening or removing targets, and calling on other guardians. Two methods for accomplishing these are altering the built environment and mobilizing law enforcement. Rather than intervening against individuals, communities may organize to eliminate contexts that attract offenders or conceal criminal acts from guardians—like rowdy bars or abandoned buildings, forms of disorder which provide criminal opportunities. Residents also use law enforcement to address crime and disorder through calls for service and demanding increased patrols or targeting of hot spots. The empirical chapters of this dissertation examine how neighborhoods regulate features of the built environment which generate criminal opportunities, and how perceived legitimacy and effectiveness of police relate to crime and collective efficacy.

1.6.4 The Situational Micro-Model of Routine Activities

Research using routine activity theory is usually concerned with aggregate variation in crime rates that result from variation in the joint the distribution of elements of criminal events. For example, if consumer goods get lighter and smaller, there will be more thefts of consumer goods, or if people spend more time away from home, more houses will be burglarized and more people will victims of street crime (Cohen and Felson 1979). In these applications, routine activity theory is typically treated as an additive model, despite its focus on crimes as convergences of elements. In an additive model, isolated increases or decreases in individual elements of crimes results in independent differences in the crime rate. In the aggregate, due to the large number of potential convergences, additive models describe the distribution of crime well—particularly those with logged outcomes (e.g., Cohen and Felson 1979:604). Despite its macro-level focus and additive applications, it is important to emphasize routine activity theory features an explicitly multiplicative micro-level model of criminal events. In a given situation, the absence of any element is sufficient to prevent the realization of a criminal incident. That is, crime cannot occur where there are no likely offenders, regardless of the number of suitable and unguarded targets. Elaborating routine activity theory in terms of its micro-model both extends the theory to smaller units of analysis and raises new problems for theorizing about situational determinants of crime.

First, crime is highly concentrated in space and time (Brantingham and Brantingham 1981). Routine activity theory may address this by drawing attention to the spatial and temporal patterning of individual convergences in targets, offenders, and guardians. To do this, however, we must consider the multiplicative (interactive) micro-model upon which the macro-level framework is constructed, and consider how, mechanistically, the micro-model relates to the macro-model. For instance, at the city or neighborhood level, more people on the streets may translate into more robbery because they serve as suitable targets. It does not follow, however, that in a specific situation, more people on a given street at a given time translates into a higher probability of robbery. The situation is dominated by interaction effects: A person alone may be a target, but additional people may serve as capable guardians. As a result, a robber might seek out a location where there is sufficient foot traffic to provide targets but insufficient traffic to provide guardianship—or where inconsistent traffic periodically produces isolated targets (St. Jean 2007:156). More people on the street may thus generate more opportunities in the aggregate, but only because their uneven spatial and temporal distribution produces individual situations conducive to crime. Heterogeneity within macro units, such as neighborhoods, may produce large variations in crime despite similar aggregate numbers of suitable targets, guardians, and likely offenders. As noted earlier, the built environment is a key source of this heterogeneity. For example, a single strip of bars and other venues for nightlife—which concentrate suitable targets when guardianship is impaired—might be the source of the majority of violent crime in a neighborhood. A situational micro-model of crime is incomplete if it does not take into account the objective physical characteristics of the built environment that generate criminal opportunities.

Second, a situational routine activity framework must consider more carefully the characteristics of actors—their roles, agency, and subjectivity. To begin, the distinction between roles can be ambiguous in a situation. A guardian or offender for one type of crime may be a target for another, and roles may be fluid, changing quickly within a situation. Roles are also problematic because they may be tautological in the micro-model. If two people are in the same location at the same time and one of them steals or damages an object, then by definition the other person is not a capable guardian. This is problematic because guardians are defined in terms of absence, and the three elements are necessary but not sufficient for crime to occur. In contrast, one cannot infer that a person who refrains from stealing an unguarded target is not a likely offender—the convergence of the offender, target, and lack of guardian does not require a crime to occur. This issue of tautology can be addressed by providing a clearer conceptualization of these roles and how they operate in situations. This requires reference to a theory of individual motivation and action.

Related to this point, routine activity theory focuses on convergences of actors in different roles generated by patterns of routine legitimate activities. This can underemphasize the agency of offenders who seek to generate these convergences and responses by potential targets who seek to minimize them. While some criminal opportunities are serendipitous (at least from the offender's perspective), others are intentionally manufactured. Agency of offenders, guardians, and potential targets is particularly important in a situational model of crime, because it produces selection into situations. For example, the broken windows mechanism by which fear of victimization produces withdrawal from public represents a process of self-selection out of routine activities in which the actor may serve as a target—and, unintentionally, also those where they might serve as a guardian. Strategic maximization or minimization of criminogenic convergences is itself a component of routine activities. In this way, individuals' perceptions of criminal opportunities shape their routine activities.

Finally, routine activities theory focuses on objective characteristics, rather than subjective characteristics as perceived by actors. This is a not problematic if the differences between perceptions and objective conditions wash out in the aggregate—that is if subjective and objective opportunities converge over time as is commonly assumed in rational choice models. The central role of individual and shared perceptions—and their divergence from objective characteristics—in both collective efficacy and broken windows theories suggest this may not be the case. In situations, perceived opportunities become more important than objective ones, though they are tethered together.

1.7 A Micro-Theory of Social Interaction Between Offenders, Targets, and Guardians

These prior points may be addressed with a micro-theory which takes into account individual perception and motivation, but also centers action in terms of interactions between actors and objects in a situation. This section draws from Matsueda and Lanfear's (2021) working paper which develops a situational micro-theory of criminal opportunity based on prior criminological work by (Giordano, Cernkovich, and Rudolph 2002; Matsueda 1992, 2006a) and the writings of American Pragmatists (Dewey 1922; Mead [1934] 2015). Following (Matsueda and Lanfear 2021), I address the role of perceptions of opportunity, the sources of motivation for actors, and the importance of the meaning of objects. While testing this situational explanation of crime is beyond the scope of the present dissertation, I discuss implications for specification and interpretation of statistical models.

This situational explanation begins by treating motivated offenders, suitable targets, and capable guardians as distinct categories which correspond to social roles. These roles come with expectations, obligations, and norms that guide individual behavior and govern interaction between individuals occupying different roles (Matsueda and Lanfear 2021:2):

> Motivated offenders tend to follow social norms of offending groups, with expectations to carry out certain crimes, and obligations to follow group norms, such as "Don't run out on a companion." The ideal suitable target lives up to the term "suitable" by generally failing to navigate dangerous streets effectively (see Sharkey 2006), such as by avoiding hot spots, dark alleys, abandoned buildings, and suspicious groups of men. Capable guardians live up to the term "capable" by exercising the capacity to prevent crime through monitoring and to intervene adroitly when criminal acts begin. For example, guardians may be residents who surveil their neighborhoods for signs of incivilities, and intervene when crimes oc-

> cur by calling out the offender, physically intervening, seeking help from others, and calling the police.

As Matsueda and Lanfear (2021) note, actors vary in in the degree to which they are motivated to offend, suitable for victimization, and capable as guardians. These characteristics are in principle measurable before actors enter a situation, and could be used to predict the resolution of a situation. Matsueda and Lanfear (2021) argue this is an overly simplistic view of the situation because all social interactions, including those involving crime, feature an element of emergence (Matsueda 2006a; McGloin, Sullivan, and Kennedy 2012; Mead [1934] 2015). Actors enter situations with a particular objective, but this objective is reshaped through interaction with other actors in the situation (Mead [1934] 2015). Luckenbill (1977) illustrates this with an analysis of homicides, in which actors with the goal of saving face escalate conflicts into lethal violence. In this way actors may enter a situation taking a particular role, but through the process of interaction, come to assume another role.

The meanings actors attribute to people, actions, and situations are important components for a theory of criminal opportunity, because objectively identical situations may be defined in different ways by different individuals (Matsueda and Lanfear 2021:5):

> For a law-abiding person with little criminal motivation, an unguarded open cash register would mean that someone should alert a sales clerk of a potential problem; for a motivated offender, it would mean that they could steal money with impunity. In other words, what is important is not just the objective opportunity, but rather the opportunity as perceived by the individual, which is based on a priori meanings actors bring into the situation, which are then shaped by the ongoing social process. In a situation of crime, when a security guard is present, offenders are likely to interpret the guard as a capable guardian, and consider the increased risk of detection.

An advantage of taking a pragmatist position is that it emphasizes socially-derived meanings that shape situational behavior. What courses of action are considered as valid solutions—both in terms of action and result of that action—and what is interpreted as problematic in the first place depends on socially-constructed meanings acquired over the life course, in particular through social interaction with others, which is structured by membership in groups.

Mead ([1934] 2015) explains how membership in groups influences individual behavior—social control—with a dual-process model of cognition similar to later developments in cognitive psychology (Kahneman 2011; see also Goffman 1972:241) . In this model, most behavior is habitual and non-reflective, and occurs in institutionalized settings. Cognitively taxing reflective decision-making is reserved for problematic situations where habitual responses fail to produce expected or desired results. When this occurs, individuals engage in an iterative process in which they consider alternative lines of action by taking the role of others, which may be actual individuals or generalized others representing entire groups with corresponding norms, expectations, and obligations (Matsueda and Lanfear 2021:6–7):

> For example, a member of a delinquent gang may be the driver as well as lookout, and when confronted with a capable guardian, may take the role of the organized gang, consider expected behavior of the role, and consequently, warn the other members of the heightened risk. Seeing the driver, the capable guardian may take the role of the community watch group and consider calling watch leader about the suspicious activity. Thus, role-taking entails taking the role of reference groups, locating their role vis-à-vis other group roles, in solving problematic situations. Note that role-taking entails taking the role of reference groups, which can be organized for crime (e.g. the delinquent gang) or against crime (e.g., the community watch) (Matsueda 2006b).

Once a problematic situation is resolved, actors incorporate the experience into the self and may use it as a guide for future behavior. As each actor enters the situation with a different self, they also take away different meanings from this experience. This process of updating the self through experience creates individual continuity and change, and, importantly, also produces shared social meanings and ultimately group social control (Matsueda and Lanfear 2021:7):

> The shared nature of experience gives rise to shared meanings, which helps to account for continuity in selves and behaviors within interaction groups. When members of a group consistently interact with each other and create or negotiate shared meanings, group identities emerge from the commonality of individual selves.
>
> The mechanism of social control, then, is self-control, in which the self—which begins with the cumulative sum of previous experiences derived from social groups and communication networks, is updated through social interaction, and influences behavior through habitual behavior and the cognitive process of role-taking (Matsueda 2006b).

Matsueda and Lanfear (2021) note two empirical implications of this perspective which are particularly relevant to the present framework. First, in stable, institutionalized settings, thinking is habitual and non-reflective and meanings are stable. Stable institutionalized settings may include neighborhoods high in collective efficacy—but also those with a strong code of the street (Anderson 1990). Norms and expectations for behavior are clear in both settings, at least for those enmeshed in local networks. Outsiders and those unaware of shared meanings may suffer consequences for violations of expectations, which may lead to rapid uptake of these shared meanings. This may contribute to the stability of these shared meanings, and thus social structures of the neighborhood, over time. These stable social meanings provide a mechanism for the regulation of group member behavior to realize collective goals—Janowitz's (1975) definition of social control.

Second, in novel situations, habits break down, actors engage in role-taking, and new meanings evolve which become available for individuals in similar future situations. Novel situations may occur as the result of an actor entering an unfamiliar location or encountering unfamiliar groups. They may also occur in familiar locations and among familiar groups when shared meanings become unstable. In broken windows theory, sudden increases in disorder destabilize norms and create fear of victimization. Here, habits which fostered effective social control, like unrestricted use of public spaces, give way to self-protective behavior, like avoiding public spaces. Gentrification may produce a similar destabilization, where unclear and conflicting expectations between newcomers and long-time residents lead to sanctioning or criminalization of previously acceptable behavior (e.g., Freeman 2006; Lanfear, Beach, and Thomas 2018).

1.7.1 Identities and Dynamics of Motivated Offenders, Suitable Targets, and Capable Guardians

As Matsueda and Lanfear (2021) describe, actors occupying each of the roles of routine activities enter situations with stable but multidimensional self, composed of a unique history of past interactions (situations) and different overlapping reference groups (generalized others):

> The selves, then produce habitual behavior in institutionalized settings and enter into cognition via role-taking in problematic situations. Symbolic interactionists use the term role-identities to emphasize that selves correspond to roles within a generalized other, and specify that identities vary across different dimensions such as commitment and salience Heimer and Matsueda (1994), and the interaction between the two.

Variation in commitment and salience of identities—as potential offender, target, or guardian—influence role-relevant behavior (Matsueda and Lanfear 2021). Offenders with salient criminal identities and commitment to criminal roles will participate in a wide variety of offenses and offend in many situations. Those with less salient identities and weaker commitment will be easily deterred. Potential targets may develop identities as wary and streetwise, using experience and knowledge to avoid being a suitable target and effectively avoid or navigate dangerous situations. Those who do not learn protective behaviors are more likely to be victimized should they encounter motivated offenders. Objects can be suitable targets as well, and owners often purposefully imbue them with crime-relevant meanings using visible protective features to reduce their perceived suitability. When these features are common in a place, it changes the meaning of objects that are unprotected:

they stand out as vulnerable targets. Guardians also vary in salience and commitment to their role based on factors like trust in and attachment to neighbors (e.g., Sampson, Raudenbush, and Earls 1997), but also by the nature of the crime or its target (e.g., Eck and Madensen 2018). Collective efficacy may directly capture respondents' identification with the role of guardian by measuring their expectations for social control behavior by their neighbors—the generalized other of a group to which they belong. Formal guardian roles, like being a police officer, are likely accompanied by strong salience and commitment (e.g., Wilson and Kelling 1982).

These roles of motivated offender, suitable target, and capable guardian are abstractions and distinct only analytically. For individuals in real situations, roles may be fluid, changing as the situation develops. For example, Anderson's (1990) code of the street depicts "street" youth as immersed in a violence-based status system which is a cultural adaptation to concentrated disadvantage. These youth sit in the precarious circumstance of being a likely, motivated offender seeking status gains by victimizing other youth, but highly sensitive to the possibility of being a target for the status gains of others. They may embody the role of offender and initiate an altercation if they perceive the situation is in their favor, such as in a chance encounter with a situationally vulnerable target. If the tables are turned, and they perceive themselves as vulnerable to victimization, the role of target becomes salient, and they may seek to avoid conflict or deescalate. The dynamics of interactions among actors may produce unanticipated emergent outcomes, perhaps outcomes undesirable to all involved, such as when a need to save face locks actors into mutual escalation with violent consequences (Luckenbill 1977). In this example, the cultural frame of the code of the street leads actors to take the roles of motivated offender or suitable target, and additionally conditions the emergent properties of the situation.

The above example also highlights that each role of the actor exists both as an image of the self and as an image of others. Both are consequential for behavior because the meanings carry with them expectations for behavior. For example, collective efficacy reflects residents' expectations that their neighbors (a reference group to which they belong) will take the role of guardian and intervene against deviance in public places (Sampson 2012).

Prior to intervening, a resident may not view themselves as a guardian, but elements of the situation—such as the presence of an actor they interpret as a potential offender—may lead to the activation of the role. Residents who intervene do so because they perceive themselves as a guardian and those they intervene against as an offender.

Similarly, the code of street creates in actors the expectation that "street" people will be motivated offenders and, importantly, that one can reduce the likelihood of becoming their target by projecting the image of being a motivated offender yourself (Anderson 1990). This highlights that an actor takes purposeful protective measures as a result of taking the role of a suitable target, imagining their potential victimization and choosing a course of action they believe will prevent it or minimize harm (e.g., St. Jean 2007:156). For this reason, offenders seek out naïve individuals that do not perceive themselves as suitable targets, and thus do not take protective actions (e.g. Deakin et al. 2007; St. Jean 2007).

1.7.2 Selection into Situations

An analysis of interaction in situations is conditional on individuals selecting into the situation. Consequently, a situational theory is incomplete without a theory of selection into criminogenic situations (Matsueda and Lanfear 2021). The same micro-theory of the individual described above may be applied to the selection process. Rather than asking how roles relate to individual behavior within a situation, one can move to the preceding step and ask how roles relate to individuals entering particular situations. Here I also raise the built environment as an important determinant of selection into situations.

If motivated offenders have the goal of maximizing successful offending, then they will select into situations with few guardians and many targets. Research on offender decision-making suggests offenders engage in both passive and active search processes (Cornish and Clarke 1986). In the passive search process, the offender is engaged in non-criminal activities during their daily round, but may recognize and take advantage of perceived criminal opportunities they encounter. It is also possible that actors with stronger salience and commitment to the offender role may be more exposed to certain opportunities. In the active search process, the offender seeks out or creates situations where they can engage a suitable target in the absence of guardians. In St. Jean's (2007) interviews of active offenders in Chicago, offenders reported their active search processes were determined by favorable built environment characteristics, past offender successes, reputations of locations, and, for drug dealing, legitimate uses of space that provide plausible deniability and access to customers. These findings are supported by other research on offender decision-making (e.g., Cornish and Clarke 1986).

It is presumable that most actors want to avoid becoming victims of crime. Actors who recognize themselves as suitable targets should attempt to select into situations with many guardians and few offenders. An important aspect of selection for targets is that it is likely to be a secondary concern existing mainly in relation to other primary activities. That is, actors aware of the potential for victimization balance perceived risk against other goals they want to accomplish. At one extreme, actors who do not recognize themselves as suitable targets will be unconcerned with the potential for victimization and unconstrained in where they go and what they do (at least with regard to crime). These actors form the ideal suitable target (Deakin et al. 2007). At the other extreme, actors putting victimization above all other concerns will, if possible, not even leave the safety of home (e.g., Wilson and Kelling 1982). Most people lie somewhere between these extremes, avoiding what they perceive to be high risk situations while engaging in a daily round that satisfies their needs for sustenance and leisure. Variation in exposure to risk is a primary mediator linking sociodemographic characteristics of individuals to rates of victimization (Hindelang, Gottfredson, and Garofalo 1978).

Motivations for guardians—and thus their selection into situations—is complicated by wide variation in actors who might assume the role of guardian. The police and security guards, for instance, have a clear motivation to select into criminogenic situations to maximize their ability to prevent crime and apprehend offenders. Other guardians with formal roles include owners and employees whose guardianship is closely connected to a particular business and perhaps the surrounding area (Eck and Madensen 2018). Their selection into situations is governed mainly by other concerns—the regular operation of the business.

Some actors who may otherwise be considered offenders may select into some situations as guardians. For example, Tita and Ridgeway (2007) find gangs defending their turf provide guardianship against rival gang members and robbery offenders. For potential informal guardians, such as people at home or on their daily round, selection into situations where they serve as a guardian may often be unintentional—unless intertwined with concerns over being a suitable target, such as staying home if concerned about burglary or joining a neighborhood watch patrol when worried about rising neighborhood crime rates.

The built environment is an important determinant of selection into criminogenic situations. Locations of employment, amenities, and services—grocery stores, banks, schools, parks—have physical locations. The daily rounds of people require that they visit these locations and also travel through locations between them. Even if a particular location is perceived to pose a high risk of victimization, actors may still select into that location because they need what is provided at that location and they have limited alternatives. Motivated robbery offenders take advantage of the need for suitable targets to visit particular locations, especially those attracting customer carrying cash and other values (St. Jean 2007). Motivated offenders may also select into locations which have few legitimate uses, like vacant lots and abandoned buildings, as they can be used to conceal illicit transactions and objects like firearms from capable guardians (e.g., MacDonald, Branas, and Stokes 2019). Chapter 2 of this dissertation examines a response to this form of selection: When residents recognize particular places as generators of criminal opportunities, they may organize to remove them, thus eliminating that context as a possibility for actors to select into.

1.7.3 Empirical Implications for Macro-Analyses

In this final section, I consider three sets implications for macro-analyses of crime derived from the situational perspective, specifically those related to differences between perceived and objective opportunities, macro-micro mechanisms, emergence, and micro-macro mechanisms.

Perceived versus Objective Opportunity

The empirical chapters of this dissertation feature analyses of data aggregated to the block and neighborhood level, in particular objective measures of opportunity. This chapter, in contrast, focuses on the situation, and posits that opportunities perceived by potential offenders are a key determinant of outcomes in potentially criminal situations. An important question is, how are perceived opportunities related to objective opportunities? Matsueda and Lanfear (2021) suggest three possibilities, each with consequences for models at the macro level: (1) perceived and objective opportunities may be perfectly correlated, in which case macro-analyses regressing crime on objective opportunities will produce unbiased estimates; (2) perceived and objective opportunities may be unrelated—which is highly unlikely—in which case macro-analyses regressing crime on objective opportunities will on average find no relationship; or (3) some potentially complex process relates objective opportunities to perceived opportunities. For example, perceived opportunities may be updated in a Bayesian fashion based on new information, resulting in more accurate perceptions for more experienced actors (Matsueda and Lanfear 2021; see also Matsueda, Kreager, and Huizinga 2006).[3]

If this third possibility is true it may violate an assumption of macro-models of criminal opportunity. Aggregate studies of criminal opportunity focus on variation in objective opportunities as a cause of variation in rates of crime (e.g., Cohen and Felson 1979). These studies implicitly assume differences between perceived and objective opportunities "wash out" in the aggregate. If the correspondence between perceived and objective opportunities is imperfect, the effect of opportunity on crime will be underestimated. Further, if this

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[3]That actors update their perceived opportunity based on experience does not guarantee that perceived opportunities converge toward objective opportunity over time. For example, Opp (1997) suggests that in contexts where objective opportunity is high but perceived opportunity is low, updating may not occur because offenders will not attempt crime. Conversely, where perceived opportunity is high but objective opportunity is low, updating will happen quickly because offenders will be sanctioned with high certainty. Asymmetrical updating may provide a mechanism by which high collective efficacy neighborhoods maintain low crime rates absent interventions if, regardless of objective opportunity, perceived opportunity is so low that offenders are deterred absolutely (e.g., Sampson 2012). If this is true, it presents the interesting possibility of a fragile equilibrium. If both residents and potential offenders base their estimation of high collective efficacy (and thus low opportunity) on the absence of crime, despite the actual capacity for control being weak, the neighborhood may be vulnerable to an information cascade in which a successful offense reveals greater than expected opportunity, which induces further offending, and so on, causing both an increase in crime and a drastic reduction in perceived collective efficacy.

correspondence varies across actors, groups, and geographies, then estimated effects of differences in the distribution of objective opportunities will be conflated with differences in the distribution of meanings relevant to the perception of opportunity.

Relaxing the assumption of correspondence between perceived and objective opportunity in macro-analyses could be approached either by directly measuring perceived opportunities or by using membership in groups as a moderator for objective opportunities. These approaches are complementary, as measures of perceived opportunity may be used to identify group differences in the divergence between perceived and objective opportunity. Matsueda and Lanfear (2021) hypothesize that perceived and objective opportunities will be strongly correlated in homogenous groups in highly-institutionalized criminal contexts and weakly correlated in heterogeneous groups in novel situations. Appendix C tests whether collective efficacy—which, when high, may reflect a highly-institutionalized but non-criminal context—moderates the effect of built environment features on crime. I find weak evidence for this moderation effect.

Macro-Micro Mechanisms and Emergence

Social structural theories of neighborhood crime imply differences in outcomes of situations across groups and neighborhoods. Otherwise identical configurations of motivated offenders, suitable targets, and capable guardians are expected to yield different situational outcomes based on the context of these social structural features. This represents a macro-micro link in which these social structural features make certain outcomes more or less likely to occur—such as promoting or discouraging violent escalation—by patterning norms, expectations, and resulting habitual behavior.

The framework on police efficacy presented in Chapter 3 provides an example. I hypothesize that in a neighborhood where the police are perceived as efficacious, motivated offenders are more likely to be deterred by the threat of sanctions by residents, because they recognize the potential for the resident to escalate the confrontation by invoking the police. The same offender might ignore the sanction or retaliate against the same guardian in a context where police are collectively viewed as less efficacious. I test this contextual effect at the aggregate level by predicting crime using an interaction between police efficacy and collective efficacy, and find modest evidence for a multiplicative protective effect. A stronger test could be made using data on risk perceptions of (potential) offenders, or perhaps using vignette experiments that test the effect of informal control on willingness to offend while manipulating perceived police efficacy.

Beyond impacting what occurs in situations by structuring habitual behavior, differences in social structure may pattern situational emergence (Matsueda and Lanfear 2021). Emergent effects arise when interactions between actors result in outcomes that are not predictable given their individual biographical histories. If criminogenic emergence is non-randomly distributed across aggregate units, it may induce bias in models which assume the outcomes of situations are a function only of the characteristics of actors (whether additive or multiplicative). Similar to differences in perceived and objective opportunity, Matsueda and Lanfear (2021) hypothesize that emergent properties should be minimal where actors or homogenous and interactions are institutionalized and habitual. Among heterogenous actors and in novel situations, interaction processes will generate unexpected outcomes. If this is true, the degree of emergence in situations will be related to community social structure. Forms of community social organization which promote institutionalized interactions—whether pro-crime or anti-crime (Matsueda 2006b)—will generate more predictable situational, and thus aggregate, outcomes. Emergence may also be consequential where neighborhoods diverging in social organization border one-another. Even if these neighborhoods are relatively homogenous internally, mobility across porous borders may generate novel interactions between heterogenous actors. This will result in emergent properties dependent on the overall spatial patterning of neighborhood social structural characteristics.

Micro-Macro Mechanisms

Just as shared meanings may influence what occurs in situations, what occurs in situations contributes to shared meanings. For example, the code of the street represents shared meanings that govern how situations involving status conflict unfold, but those shared meanings were established through the accumulation of direct and vicarious experiences of status conflict in the past. When new situations involving status conflicts unfold as participants and observers expect them to, based on their shared understanding of the code of the street, it reinforces and propagates that shared meaning. If, however, these means of satisfying status conflicts are routinely disrupted, this shared understanding may be eroded over time.

Similarly, if a homicide occurs on a particular street corner of a low-crime neighborhood, that corner may take on a powerful shared meaning. This may alter behavior in the location where the crime occurred, such as if residents avoid that corner out of fear of victimization or engage in monitoring to prevent reoccurrence, or in similar locations elsewhere in the neighborhood. It is also possible the homicide will be taken as a salient event which alters perception of the entire neighborhood—from a place safe from violence to one where violence can strike without warning. This may alter behavior across the entire neighborhood. For example, Carr (2005) describes a double homicide in a Chicago neighborhood as a salient event which changed resident perceptions of the neighborhood, resulting in mobilization against gang activity. In this way, the outcome of a single situation can have wide-ranging effects on the macro-context of a neighborhood.

Broken windows theory describes a similar micro-macro process in which individuals interpret instances of disorder as signals of elevated risk of victimization, and, as a result, select out of public spaces where they may be exposed to offenders (Innes 2004; Wilson and Kelling 1982). In theory, this produces effects on victimization which are opposite in sign at the micro- and macro-level. While the individual risk of victimization (micro) is reduced by constraining behavior, it increases the general risk of crime in the area (macro) by reducing the number of potential guardians in public spaces (Bellair 2000). This and the prior examples suggest complex multi-level dynamics which may be obscured in single-level and cross-sectional research designs. Future research should explore these relationships using repeated observations of individuals nested in neighborhoods, ideally with independent data on crime.

1.8 Conclusion

This chapter attempted to accomplish two related goals. In the first part of this chapter, I provided an overview of the theories used in the empirical chapters of this dissertation: collective efficacy, broken windows, and routine activities. While often treated as competing explanations for crime, these theories are largely complementary in their causal mechanisms. They also share a reliance on incompletely articulated micro-models of situations and individual behavior, in particular unexamined perceptual mechanisms. In the second part of this chapter, I proposed a framework for integrating these theories into a multi-level situational explanation for crime using a pragmatist micro-theory (Matsueda and Lanfear 2021). The purpose of this framework is to specify the social mechanisms left unarticulated in these social structural theories. This framework draws attention to the importance of individual roles and meanings, selection into situations, and causal links between situations and macro characteristics of neighborhoods and groups. In doing so, it connects the macro-structural theories of neighborhood crime to a broader literature, including but not limited to, cultural explanations of violence (Anderson 1990), situational models of crime (Luckenbill 1977), criminal opportunity (St. Jean 2007; Wilcox and Cullen 2018), and perception and interpretation of disorder and crime (Harcourt 2001; Innes 2004).

While I propose situational mechanisms for neighborhood social structural characteristics, the present dissertation cannot test these mechanisms directly—though my findings are consistent with the theory presented. This chapter serves as a necessary first step of specifying social interactional mechanisms for a neighborhood theory of social structure and opportunity and considering their implications for empirical studies. The next step is clearly specifying propositions that arise from this framework and subjecting them to empirical tests.

Chapter 2

COLLECTIVE EFFICACY AND THE BUILT ENVIRONMENT

2.1 Introduction

Crime is highly concentrated in particular urban neighborhoods (Shaw and 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, and 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 2012:156–60). 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, and Earls 1997).

Just as crime is concentrated in particular neighborhoods, within neighborhoods crime is concentrated in particular locations—hot spots (Sherman, Gartin, and Buerger 1989; Weisburd, Groff, and 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 and 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 and 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.

2.1.1 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 and 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 and Felson 1979; see also

Brantingham and 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 and 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 and 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 and 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, and Beach 2020; Sampson and 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 and Felson 1979; Wilcox and 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, and Stokes 2019), liquor stores and bars precipitate assaults and provide vulnerable targets for robberies (Pridemore and 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 and 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 and Eck 2011) or, like recreation facilities, by promoting unstructured socializing of youth (Osgood et al. 1996; Weisburd, Morris, and Groff 2009). These are, of course, only a selection of examples. The literature on opportunity and the built environment is voluminous (Wilcox and Cullen 2018).

These criminogenic built environment characteristics may even be more consequential than factors like residents' capacity for social control. For example, St. Jean (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.

2.1.2 Control of the Built Environment

The built environment is shaped by the actions of local government in conjunction with developers and property owners (Logan and 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 both 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 and 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 2005:121–23). 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 and Grasmick 1993). Collective efficacy is thought to predict political mobilization to influence external institutions (Sampson 2012:152–53), 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, and 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 and 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 2012:159–60): 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 build environment. Efficacious neighborhoods can turn attempts at development into extended, costly battles (e.g., Einstein, Glick, and 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 and Molotch 2007:113). 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. These may occur if some features foster social ties and cohesion—building blocks of collective efficacy—by increasing interaction between residents (Small and 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 and 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 and Molotch 2007). Einstein, Glick, and Palmer (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 and 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.

2.1.3 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:
   a. 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).
   b. Features which reduce inhibitions, precipitate conflicts, or conceal weapons and illicit market transactions, such as abandoned buildings, bars, and vacant lots, will promote violence.
   c. 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 2.1 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 ones, find null effects, which may be a function of insufficient variation over time in collective efficacy (Lanfear, Matsueda, and Beach 2020). Testing this direct effect is not a

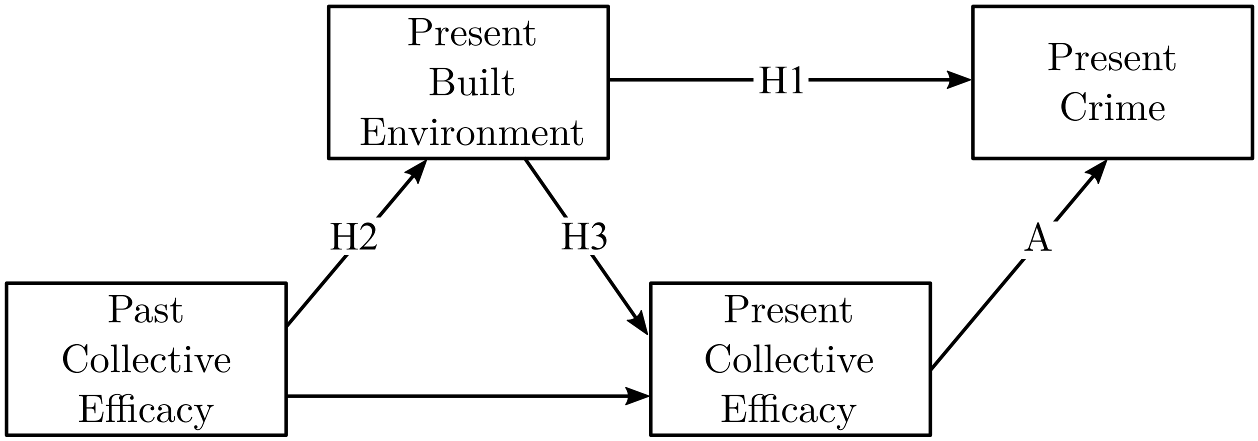


Figure 2.1: Theoretical model of collective efficacy, the built environment, and crime. Tested hypotheses represented as paths H1, H2, and H3.

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 chapter 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, but Appendix B contains a more detailed discussion.

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 and 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 unlikely to be identified. 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 and 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, and Swanstrom 2014; Logan and 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, and Earls 1997). Conventional measures of collective efficacy are designed to capture informal social control capacity. However, I am 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.

2.2 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 et al. 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] 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 2012:78–80; Sampson, Raudenbush, and Earls 1997:919). 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, and 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, and Earls 1997).

Neighborhoods sociodemographic structure is a primary determinant of crime rates, and

[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.

collective efficacy mediates a large portion of this relationship (Sampson, Raudenbush, and 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, and 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, and Stults 2014). The LTDB normalizes census tract boundaries over time to ensure measures in longitudinal studies describe the same units over time.[2] 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.[3] 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 and Grasmick 1993; Shaw and McKay [1969] 1942). See Appendix A 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

[2]Chicago is a unique city, however, in that its census tract boundaries have remained largely fixed since the 1920s. Use of non-normalized data likely will produce identical results in Chicago.

[3]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 those from Sampson, Raudenbush, and Earls (1997).

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 the 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 2.2 depicts the sampled blocks and neighborhood clusters. Note that most blocks are isolated or adjacent to few other blocks.

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 and Eck 2011). It may be the case that many features are comparably criminogenic, but removal efforts are concentrated

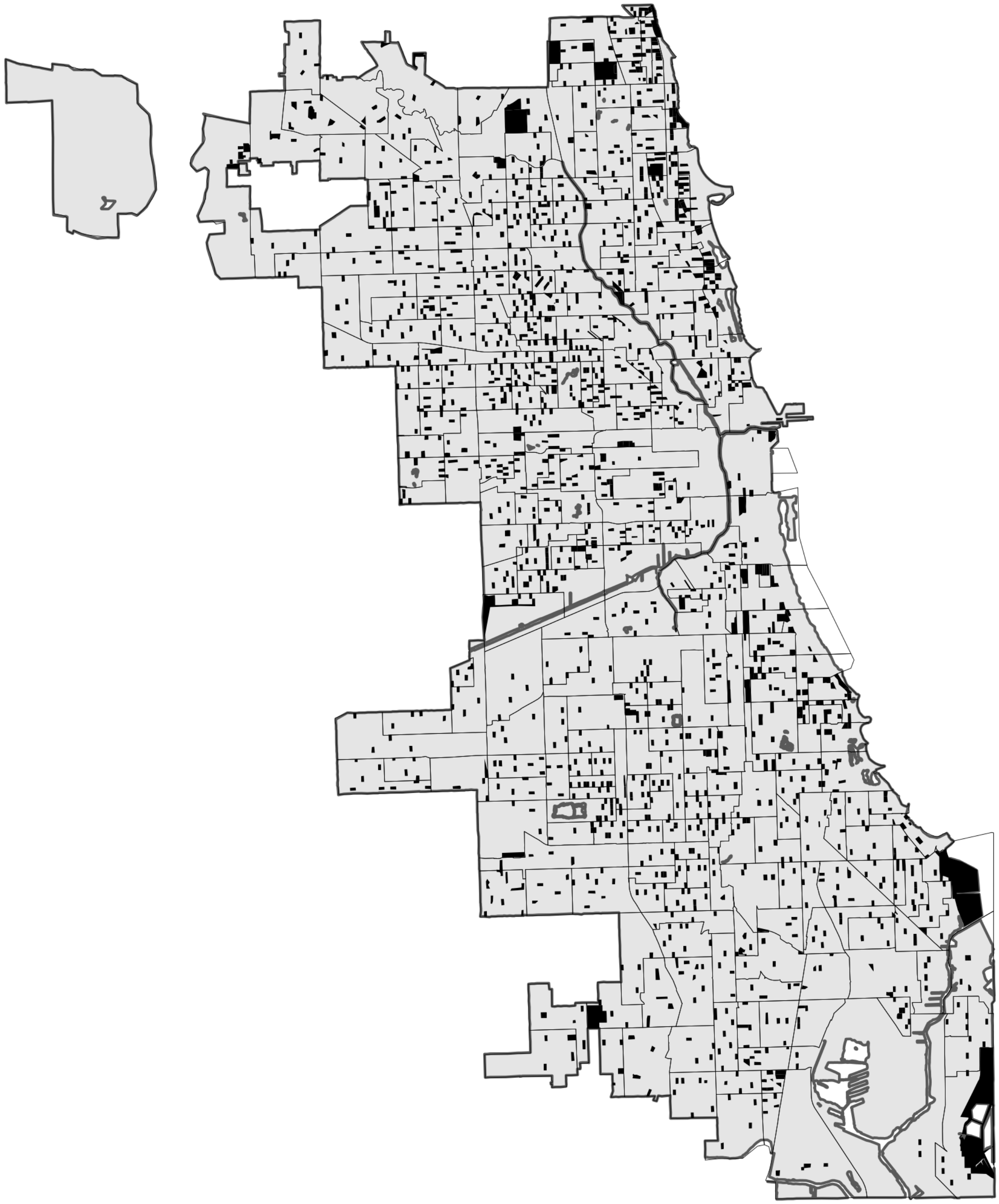


Figure 2.2: Map of census blocks sampled in 2001-2003 Chicago Community Adult Health Study. Sampled blocks are filled black shapes. Neighborhood clusters are outlines.

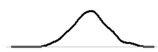
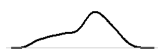
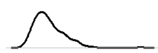
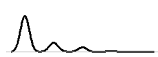
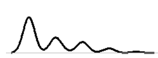
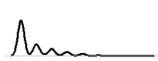
on those features perceived as particularly undesirable or unambiguously problematic.

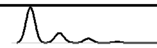
For an analysis of the impact of past collective efficacy on the built environment, I construct a past collective efficacy measure from the 1995 PHDCN community survey (PHDCN-CS). I estimate this measure using the same multilevel approach as for the CCAHS. The PHDCN-CS is similar to the CCAHS's community 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, and Buerger 1989; Weisburd, Groff, and 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 2.1 presents descriptive statistics for these data.

Table 2.1: 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

Measure	Mean	SD	Min	Density	Max
Vacant	0.12	0.21	0.00		1.00
Density (Block)	10.85	7.59	0.00		83.42

2.3 Methods

I examine the relationships between collective efficacy, the built environment, and crime using a system of piecewise structural equations (see: Figure 2.3) 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 2.3 is a simplified version of the complete structural model. Each solid ar-

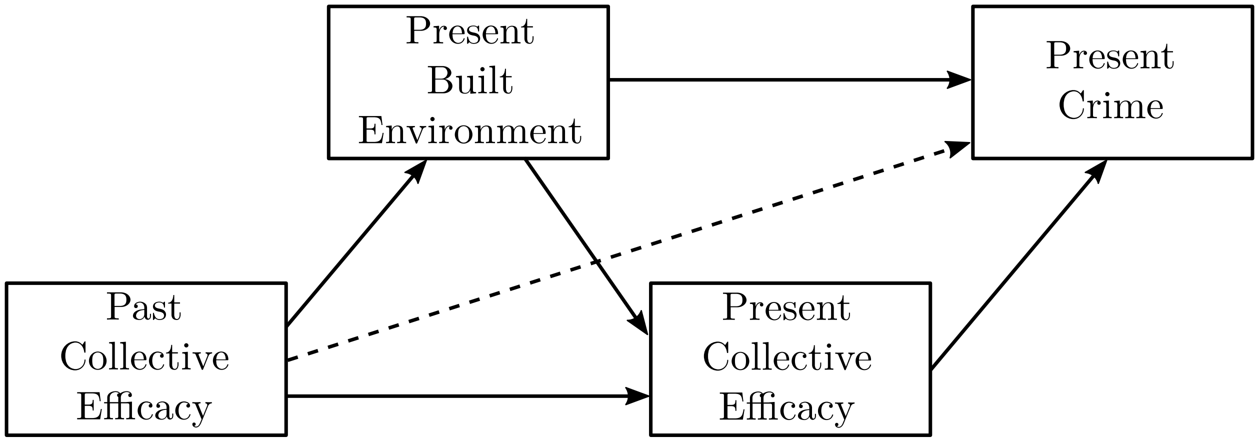


Figure 2.3: Longitudinal structural model. Dashed arrow represents tested independence restriction (d-separation).

row represents separate model or set of models testing the hypothesized causal pathways. 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 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 2007:156). 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, and 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 2.2 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).

2.3.1 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 2.4 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.

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 et al. 2015). Cluster intercepts address correlations in residuals for blocks in the same neighborhood. Conditional on the included

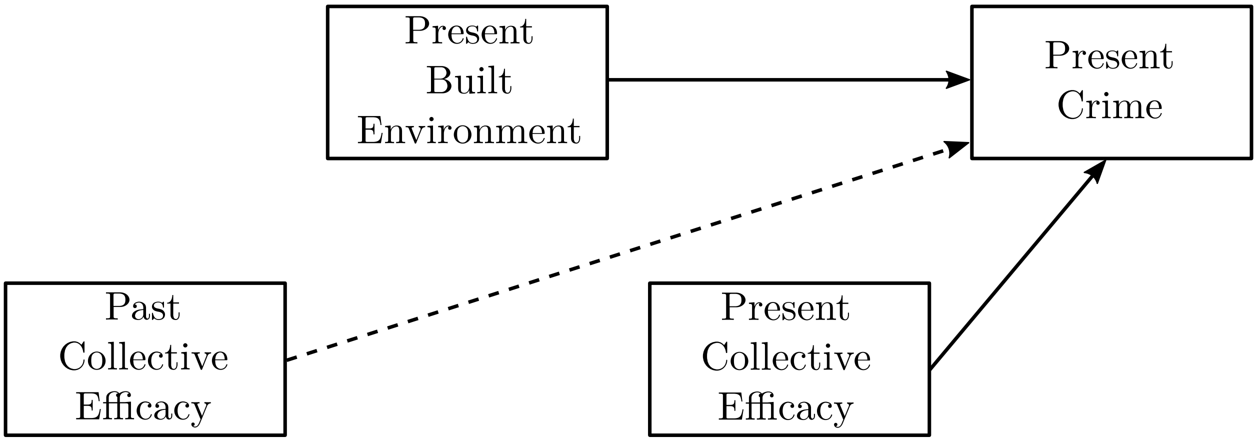


Figure 2.4: Simplified depiction of crime models. Solid arrows are modeled direct effects. The dashed arrow represents unmodeled (restricted) paths.

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.

2.3.2 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 2.5 depict the tested relationships.

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

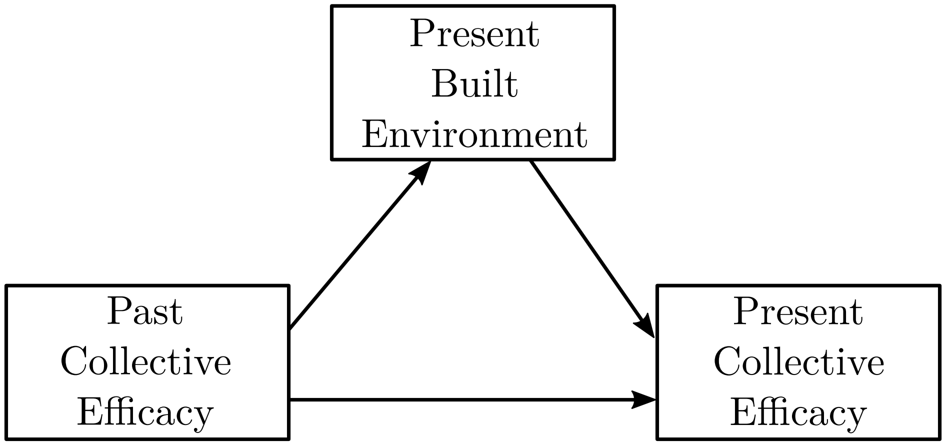


Figure 2.5: Models of the built environment and present collective efficacy.

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.

2.4 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.

2.4.1 Crime Results

Figure 2.6 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 otherwise similar block. The most notable result in Figure 2.6 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

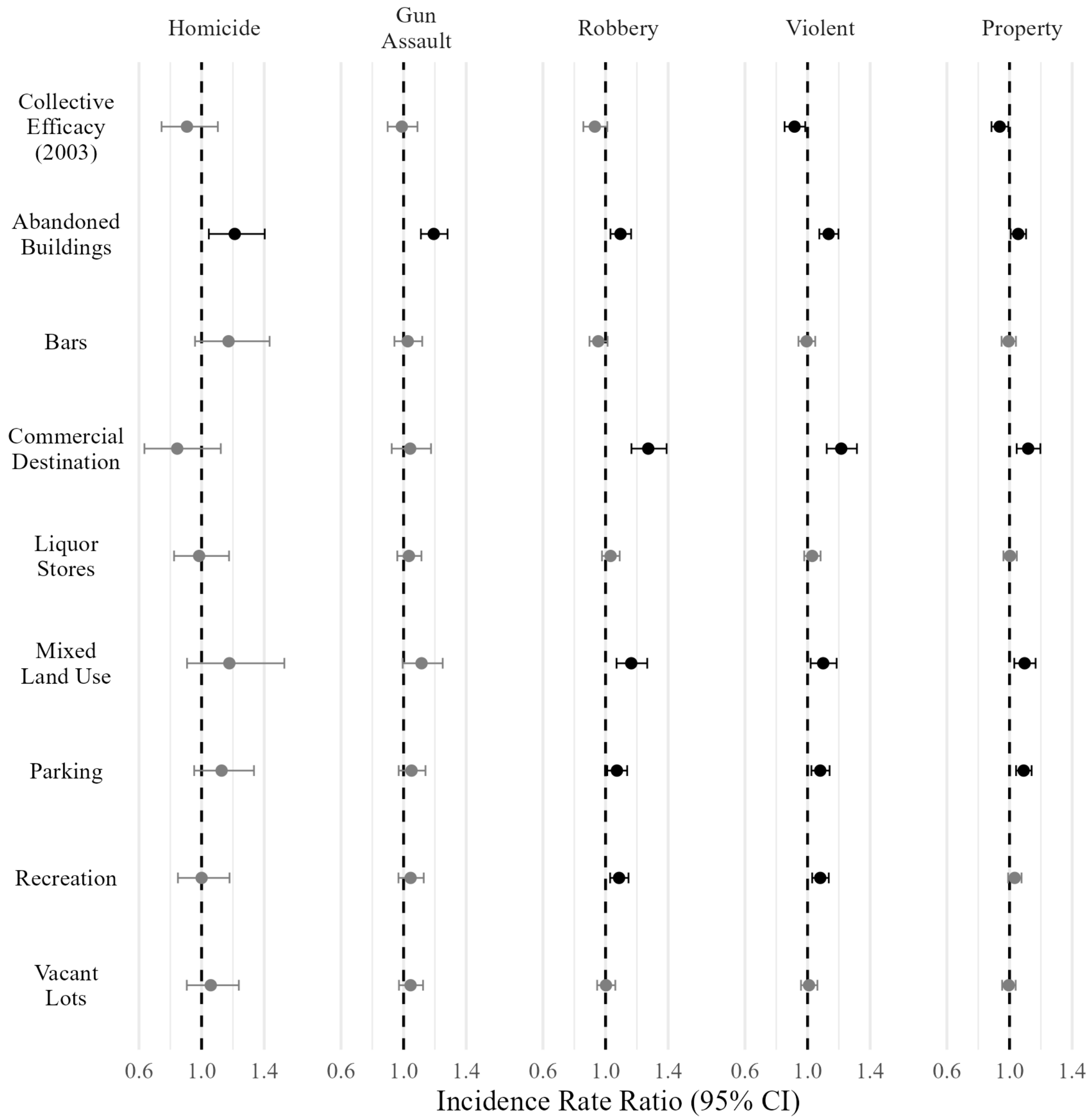


Figure 2.6: Estimated incidence rate ratios and 95% confidence intervals for selected predictors of five crime types. Predictors are standardized, outcomes are log-counts. Estimates significant at $p < .05$ are in black.

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 et al. 2006). The present research design is unable to examine potential heterogeneity of this sort. Appendix C 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 2.2 below. These estimates are the log-count marginal effects on crime from one standard deviation differences in predictors. R^2 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 2.6 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 $C = 9.99$, $df = 10$, $p = 0.44$). This result is consistent with the expectation, shown as a dashed line in Figure 2.4, that past collective efficacy exerts no protective effect on crime except via present collective efficacy or the built environment.

Table 2.2: Negative binomial estimates of crime.

Predictor	Homicide	Gun Assault	Robbery	Violent	Property
Neighborhood					
Coll. Eff	-0.10	-0.01	-0.07	**-0.09**	**-0.07**
(2001)	(0.10)	(0.05)	(0.04)	**(0.04)**	**(0.03)**
Disadv.	**0.56**	**0.70**	**0.22**	**0.39**	**-0.08**
	(0.11)	**(0.06)**	**(0.04)**	**(0.04)**	**(0.03)**
Stability	-0.04	-0.02	**0.16**	**0.14**	**0.30**
	(0.13)	(0.06)	**(0.05)**	**(0.04)**	**(0.03)**
Hispanic /	**-0.36**	**-0.16**	**-0.41**	**-0.33**	**-0.23**
Immigrant	**(0.11)**	**(0.05)**	**(0.04)**	**(0.04)**	**(0.03)**
Density	**0.23**	0.07	**0.25**	**0.16**	**0.09**
(Neighb.)	**(0.11)**	(0.06)	**(0.05)**	**(0.04)**	**(0.03)**
Block					
Abandoned	**0.19**	**0.18**	**0.09**	**0.13**	**0.05**
	(0.07)	**(0.04)**	**(0.03)**	**(0.03)**	**(0.02)**
Bars	0.16	0.03	-0.05	-0.01	-0.01
	(0.10)	(0.04)	(0.03)	(0.03)	(0.02)
Commercial	-0.17	0.04	**0.24**	**0.19**	**0.11**
Dest.	(0.15)	(0.06)	**(0.04)**	**(0.04)**	**(0.03)**
Liquor	-0.02	0.03	0.03	0.03	0.00
	(0.09)	(0.04)	(0.03)	(0.03)	(0.02)
Mixed Use	0.16	0.11	**0.15**	**0.10**	**0.09**
	(0.13)	(0.06)	**(0.04)**	**(0.04)**	**(0.03)**
Parking	0.12	0.05	**0.07**	**0.08**	**0.09**
	(0.09)	(0.04)	**(0.03)**	**(0.03)**	**(0.02)**
Recreation	0.00	0.04	**0.08**	**0.08**	0.03
	(0.08)	(0.04)	**(0.03)**	**(0.02)**	(0.02)
Vacant	0.06	0.04	0.00	0.01	-0.00
	(0.08)	(0.04)	(0.03)	(0.03)	(0.02)
Density	0.07	0.12	**0.10**	**0.18**	**0.10**
(Block)	(0.16)	(0.06)	**(0.04)**	**(0.03)**	**(0.03)**
Density	**-0.60**	**-0.35**	**-0.09**	**-0.13**	**-0.05**
(Block)^2	**(0.21)**	**(0.08)**	**(0.03)**	**(0.03)**	**(0.02)**
Past Coll. Eff.	0.48	0.23	0.92	0.13	0.52
d-Sep. P-value					
R2	0.14	0.17	0.28	0.36	0.29

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 and Eck 2011). A more convincing test would require measures of the stocks or flows of people at the block level (see Browning, Pinchak, and Calder 2021).

2.4.2 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 2.3. Table 2.3 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 $p < .05$ are bolded. R^2 values are conventional for collective efficacy (single-level model) and marginal for all others.

Table 2.3: Linear model estimates of built environment features and collective efficacy.

Predictor	Collec. Effic.	Abandoned	Bar	Commer. Dest.	Liquor	Mixed Land Use	Parking	Recreation	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	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 $(\text{Block})^2$	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

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.[4] 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, and 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).

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[4] 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.

2.5 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, and 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 2012:173–77). 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, and 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 and 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 and 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, and 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 2012:159–61 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 and 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 and Goldstein 2018). Interventions in the built environment are a promising alternative to increased policing for addressing crime in disadvantaged neighborhoods, particularly serious violence (Kondo et al. 2018). Remediation of criminogenic features of the environment is often inexpensive, effective, and politically feasible—and generates benefits beyond crime control (MacDonald, Branas, and 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 Appendix C). 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, and Hunt 2003). For example, the impact of alcohol outlets on crime appears conditional on neighborhood social structures (Pridemore and 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 et al. 2006). More broadly, efficacious place management is a major source of heterogeneity of criminogenic effects between otherwise similar places (Eck and 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 and 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, and 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 and 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, and 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 and 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, and 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 and Molotch 2007; MacDonald, Branas, and Stokes 2019). This may be an important mechanism by which collective efficacy promotes stable, safe, and livable neighborhoods.

Chapter 3

COLLECTIVE EFFICACY AND FORMAL SOCIAL CONTROL

3.1 Introduction

The goal of this chapter is to interrogate the role of resident perceptions of police effectiveness and legitimacy in the neighborhood social control system of collective efficacy theory. Collective efficacy is a neighborhood's capacity for achieving an intended effect, such as regulating child behavior or maintaining public order (Sampson, Raudenbush, and Earls 1997). Some authors describe collective efficacy as in part the result of perceptions of legitimate, effective, and responsive policing—police efficacy. When police efficacy is high, it promotes collective efficacy resulting in residents being more likely to engage in acts of informal social control (Drakulich and Crutchfield 2013; Silver and Miller 2004). Sampson (2012; Sampson, Raudenbush, and Earls 1997), however, describes collective efficacy as the ultimate source for all forms of neighborhood social control, including both informal control actions by residents and calls to police for formal control actions. This suggests efficacious policing is promoted by collective efficacy rather than vice versa.

In attempting to adjudicate between these two theories, I ask the question: Does efficacious policing foster collective efficacy, or does efficacious policing depend on the collective efficacy of the community? Additionally, I examine the possibility that collective efficacy and police efficacy reinforce one-another, yielding multiplicative effects on crime. In approaching these questions, I consider how social contexts like collective efficacy and police efficacy may influence how individuals respond to the unwanted behavior of others.

3.1.1 Collective Efficacy and Police Efficacy

Research on collective efficacy asserts informal social control is a primary mechanism by which neighborhoods regulate crime and deviance (Sampson 2012:152). Collective efficacy is frequently used to operationalize the capacity for informal social control (Lanfear, Matsueda, and Beach 2020), which manifests mainly as actions by neighborhood residents like monitoring and direct intervention against deviance and public disturbances (Sampson, Raudenbush, and Earls 1997). It is claimed that collective efficacy also affects crime by increasing the propensity of residents to call the police (Sampson 2012:152; Sampson and Raudenbush 1999). In the context of collective efficacy, Sampson and Raudenbush (1999:612) state, "actions of informal control need not … exclude the police or other formal channels of recourse." What marks this as informal control, from their description, is that it is resident-initiated. The overwhelming majority of police contacts are, however, initiated by calls for service (Black 1971; Gottfredson and Gottfredson 1988). If the invocation of police by neighborhood residents is included under the umbrella of informal control, it narrows what may be considered formal social control to proactive policing. It also broadens informal social control to include the majority of police interactions with the public.

I argue a distinction should be made between actions of formal and informal social control, because they are alternate methods for solving problematic situations. Informal control actions are the result of individuals without a formal role assuming responsibility for the regulation of others' behavior in a given situation. In contrast, when someone calls the police, they are invoking an agent of the state with a formal role that charges them with legal authority to resolve a situation and the corresponding capacity to use violence for this purpose (Wilson and Kelling 1982). By invoking the police, the individual who initiates the call defers responsibility for handling the situation to others. This distinction is important because the decision to defer responsibility is likely based in part on the individual's belief the police will be responsive, effective, and fair in their treatment (Tyler and Fagan 2008–2009). Past research indicates these beliefs about effectiveness and legitimacy of police are largely grounded in respondents direct and vicarious experiences from interactions with police (Tyler 2006; Tyler and Huo 2002). The context of decisions to invoke police may be framed as a principal-agent problem in which the potential caller is the principal and the police are the agents (Dharmapala, Garoupa, and McAdams 2016). The decision to call upon the police is determined by considerations like the perceived effectiveness of these agents in resolving the situation and the potential for unintended harm that their involvement carries. While both formal and informal control may be initiated by residents—and may even be seen as substitutes by those residents—they are not equivalent in their availability, effectiveness, or consequences.

The distinction between capacities for formal and informal control has already been made in the literature examining collective efficacy and police efficacy (e.g., Drakulich and Crutchfield 2013; Silver and Miller 2004). In this literature, collective efficacy is usually assumed to capture informal control capacity and is treated as the primary proximal determinant of neighborhood variation in crime and deviance. Formal social control capacity is assumed to precede collective efficacy. For example, Silver and Miller's (2004) cross-sectional analysis found satisfaction with police was a strong predictor of neighborhood collective efficacy in Chicago, suggesting effective policing increases informal social control capacity. Causal order in that work was made by assumption, based on the belief that "residents are [unlikely] to base their perceptions of local police on their neighbors' social control behaviors" (Silver and Miller 2004:574). This is a plausible assumption, but it is also an empirical question whether perceptions of police are causally descended from collective efficacy. They also did not attempt to evaluate the effects of collective efficacy and police efficacy on crime, a task taken up in this analysis.

Drakulich and Crutchfield (2013) reported similar results using data from Seattle, and found police efficacy explained the association between neighborhood racial composition and collective efficacy. Police efficacy, they assert, fosters collective efficacy by reducing the perceived costs of engaging in informal social control. Experiences with and perceptions of procedural injustice produce lower police efficacy in neighborhoods with larger minority populations. This translates into reduced informal control capacity. As with Silver and Miller (2004), Drakulich and Crutchfield (2013) do not examine the effects of police efficacy and collective efficacy on crime, nor do they consider the opposite causal ordering: collective efficacy precedes police efficacy.

In contrast to the literature placing police efficacy as a precursor to informal social control, the systemic model of social disorganization casts formal social control as concurrent to informal social control (Bursik and Grasmick 1993). The systemic model describes the neighborhood system of social control as consisting of interlocking levels which are loosely connected or "articulated": private, parochial, and public social control. They are separate, drawing on different sources, operating through different actions, and sometimes responding to different problems. All levels must be present and working in coordination with the others for the system to function properly and maintain low rates of crime. In the systemic model, the direct intervention and monitoring actions most often associated with collective efficacy are part of parochial control. When residents call the police, however, they invoke agents who exert actions of public social control.

Sampson and Raudenbush (1999:612) link collective efficacy to this multi-pathway systemic model, but emphasize the agency of neighborhood residents as the key causal force. From this perspective, there are separate private, parochial, and public levels of social control, but all are initiated by individual and collective action of residents. Collective efficacy captures not just the capacity for direct informal control but the general capacity of a neighborhood to activate any pathways of social control. This suggests collective efficacy is an antecedent to the use of formal social control. The impetus for social control may come from residents, but the police may be used to address situations which residents may perceive as too risky for direct intervention or otherwise not their responsibility. Despite describing this causal sequence, the authors have not, to my knowledge, explored this empirically. This connection seems straightforward, however, as most policing occurs in reaction to a citizen calls for service, so citizen intervention is a necessary starting point (Black 1971; Gottfredson and Gottfredson 1988). If collective efficacy predicts monitoring and reporting behavior by residents, it will result in more frequent and rapid police responses. Thus, collective efficacy may precede subjective perceptions of effective policing because it increases the objective effectiveness of policing with regard to reducing crime and other incidents perceived as problematic to residents.

Carr's (2003, 2005; 2012) "new parochialism" reflects a similar causal ordering. In his study of a middle-class white Chicago neighborhood, he found residents engaged in informal social control activities—parochial control—that were facilitated by external organizations and formal authorities—public social control agents. When residents initiated action, they used formal authorities as a buffer between themselves and problems in their communities, in part due to the perceived costs of intervention. The residents of Carr's (2005) study reported that this shift toward hybrid parochial and public social control was a recent change due to broad shifts in the context of control, such as heightened fear of gangs and drug crime, reduced informal monitoring capacity due to dual-income households with long work hours, and declining acceptability of sanctioning others' children for misbehavior. These changes led residents to rely on structured and safe methods of engagement. These findings are important for the present work because Carr's study was conducted in Chicago in 1993 through 1999—the same city and period in which the data used in this work were collected.

3.1.2 Collective Efficacy, Police Efficacy, and Mechanisms of Social Control

Sampson (2012) proposes that collective efficacy captures the general capacity for social control in neighborhoods. Formal and informal control represent different forms of activation of this capacity. Figure 3.1 is a simplified illustration of this model. The question, then, is what predicts the use of different forms of activation, and how are they related to crime control? If our interest is only in the overall effect of collective efficacy, this question may be inconsequential: all methods of control are only mechanisms for collective efficacy. If, however, we wish to decompose this total effect or we expect other factors to influence the effects of different pathways, we must consider the differences between acts of informal and formal social control and the roles of actors that perform each.

Collective efficacy is typically measured using a scale of survey responses by residents describing both their expectations that their neighbors would intervene against deviance and their belief that norms and values are shared among those neighbors (Sampson, Raudenbush, and Earls 1997). Despite capturing expectations for intervention, the

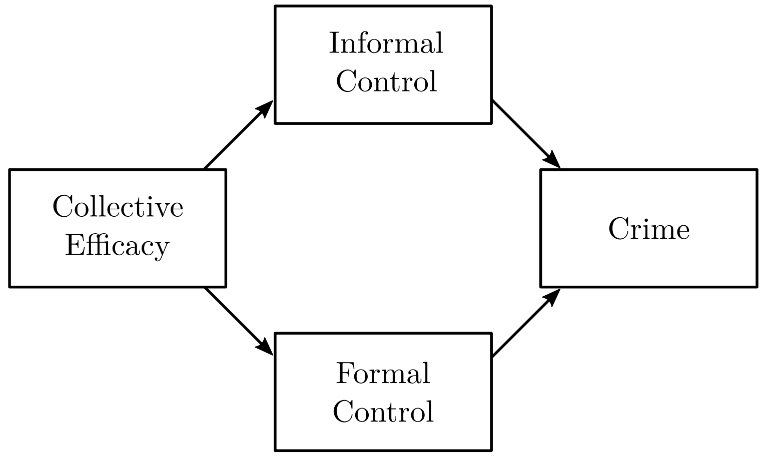


Figure 3.1: Collective efficacy as capacity for informal and formal control actions.

form those interventions might take is not specified. These indicators thus tap shared beliefs about the actors that initiate any social control actions in a neighborhood, actors who, importantly, are also those performing the actions of informal social control.[1] While collective efficacy does describe the actors that typically initiate formal social control, it does not tap residents' beliefs about the actors that, once invoked, carry out those actions of formal social control—the police. Instead, police efficacy describes expectations for the behavior of these formal social control actors: beliefs about whether police will respond, and if they do, if they will be effective and fair.

If most social control actions are initiated by residents, collective efficacy may capture the propensity to activate any mechanism of social control, but police efficacy may more narrowly capture resident willingness to activate the formal social control mechanism by calling the police (e.g., Kirk and Matsuda 2011). Given the same number of situations provoking interventions, it is possible that the willingness to invoke the police may only alter the balance of actions of formal versus informal control, rather than the overall number of actions or their effectiveness. Alternatively, it is also possible that the context of police efficacy changes the calculus of intervention itself, resulting in interventions of different quality and quantity.

[1]The residents are essentially describing a generalized other of the group to which they belong.

3.1.3 Collective Efficacy in the Shadow of the Law

I argue that the neighborhood context of social control determines what individuals view as relevant means for resolving problematic situations resulting from the unwanted behavior of others. While rooted in individual perceptions, neither collective efficacy nor police efficacy are properties of individuals. Rather, they are properties of neighborhoods which reflect the shared meanings of the people who live there, and presumably to some degree also the people who visit those places, hear about them, and communicate with their residents. These shared meanings provide the social context in which actors decide how to approach problematic situations and behave within those situations.

A context of high collective efficacy is one in which people generally believe in shared norms of behavior and intervention against violations of those norms is warranted and likely to occur. A context of high police efficacy is one in which people perceive that police will intervene effectively and fairly when invoked by residents. Note that the mechanism(s) that connect collective efficacy and police efficacy to incidents of crime are ambiguous: For example, it may be deterrence or reduction in opportunity (e.g., Sampson 2012), acceptance of legitimacy of shared norms or the law (e.g., Tyler 2006), or both. While these mechanisms are important for theory and policy the present analysis neither tests nor assumes any specific mechanism for observed effects on crime. Regardless of which mechanism is operating, because police require the public to invoke them in the first place, it is unlikely they will be perceived as responsive or effective in a context of low collective efficacy where the public infrequently intervenes in problematic situations. In such a context the police can only operate proactively, and proactive policing is less likely to be perceived as effective or legitimate by residents (Fagan and Davies 2001; Tyler, Jackson, and Mentovich 2015). This may provide a direct mechanism linking low collective efficacy to low police efficacy.

Consider also the possibility that perceptions of formal social control capacity change the context, and thus the meaning, of acts of informal social control: Informal social control may exist in the shadow of the law (Mnookin and Kornhauser 1979). When informal sanctions are insufficient to stop problem behavior, invocation of formal authority provides a last resort. An offender may be deterred from committing an offense not because the informal sanction itself carries weight, but because they believe the sanctioner will call the police if ignored. Likewise, sanctioners may perceive of a situation as less risky for intervention, because effective policing makes retaliation unlikely (St. Jean 2007). Informal control lacks these buttresses where potential sanctioners are unwilling to call the police because they believe they will be ineffective or harmful, and where targets of sanctions are aware of this reluctance. Thus, absent the threat of formal control, residents may be unwilling to intervene against deviance and offenders may have little fear of sanctions. This implies moderation in which police efficacy enhances the effect of collective efficacy on crime. This may be particularly consequential in neighborhoods with large BIPOC populations that report low police efficacy (Drakulich and Crutchfield 2013; Tyler and Fagan 2008–2009). This may result in higher perceived costs to invoking police, resulting in fewer calls or calls only for serious crimes.

3.1.4 Moderation or Causal Sequence

The extant literature presents two hypothetical relationships that could occur between collective efficacy and police efficacy, which I will refer to as causal sequence hypotheses. The causal sequence hypotheses are based on the idea that informal and formal social control are not parallel problem-solving pathways, but rather links in a chain. These sequential relationships may manifest in either direction (or both at once). If effective policing emerges as a result of the general propensity of residents to intervene against crime and deviance, then police efficacy may be causally descended from collective efficacy (e.g. Sampson 2012). If willingness to engage in informal control depends on residents perceiving that they are supported by effective policing, collective efficacy may be causally descended from police efficacy (e.g. Drakulich and Crutchfield 2013; Silver and Miller 2004).

I also introduce an alternative hypothesis: moderation. The moderation hypothesis posits that informal and formal social control are separate problem-solving pathways, but the capacities for each alter the context of intervention. Residents may use either to deal with local problems, likely preferring the one perceived as more effective or appropriate in a given situation. But, the availability of alternatives—in particular escalation to formal control—changes the decision-making process for all actors involved. There are two forms this moderation may take: Reinforcing moderation, the form I anticipate, may exist if perceptions of effective policing cause offenders to treat informal sanctions and monitoring more seriously and residents to perceive lower risks to their interventions. If true, when collective efficacy and police efficacy are both high, crime and victimization will be lower than expected from an additive relationship.

There is an alternate moderation hypothesis, however. It may be the case that so long as either capacity for control is high, crime and victimization will be low. That is, social control capacities may reach a plateau where additional capacity is only surplus. This would produce a convergence in levels of crime between areas with high collective efficacy, high police efficacy, and both. This is analogous to St. Jean's (2007) finding that crime is minimal on blocks where either collective efficacy is high or social disorder is low. Pockets of crime in his study area were the result of a multiplicative convergence of disadvantage.

Temporal scale is a final consideration that has not been examined by the existing research in this area (see Taylor 2015). Prominent studies on collective efficacy and police efficacy use cross-sectional research designs (e.g. Drakulich and Crutchfield 2013; Silver and Miller 2004), which prevent examining the speed at which mechanisms might transmit causal effects between these factors. For example, collective efficacy may increase police efficacy by promoting more (and better informed) calls to police which in turn produces more effective responses. It may, however, take many incidents over a long period of time in which police are effective and procedurally just to improve the shared understanding of police efficacy in the neighborhood. Conversely, the effect of police efficacy on collective efficacy might be immediate if residents are emboldened to intervene by the belief that police responses will be effective. The literature in this area does not present strong prior expectations for the speed of causal effects. Consequently, I make no hypotheses regarding temporal scaling and model both lagged and immediate causal relationships.

Importantly, more than one of these hypothetical relationships may be present at once. There may, for instance, be moderated mediation between collective efficacy and police

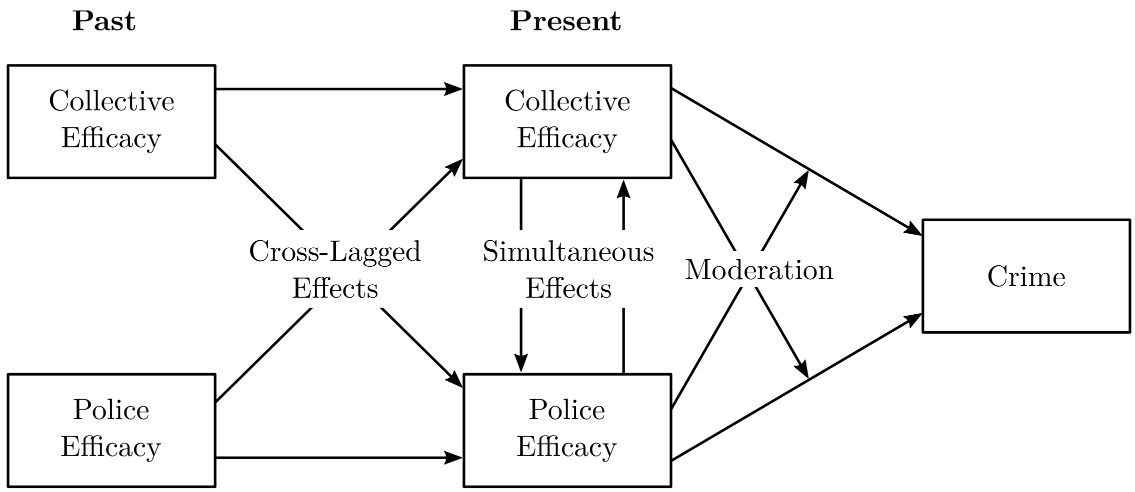


Figure 3.2: Potential effects of collective efficacy and police efficacy.

efficacy with regard to crime. For example, collective efficacy may lead to police efficacy but police efficacy may increase the effectiveness of informal social control in reducing crime. Adjudicating between different causal relations is difficult, and different assumptions may lead researchers to find support for each provided the same data. Figure 3.2 depicts a model with two time periods (past and present) where all hypothesized relationships between collective efficacy and police efficacy are present. Crime and simultaneous effects are omitted in the past period for simplicity. Cross-lagged effects represent gradual causal processes, while simultaneous effects represent relatively fast causal processes. Moderation is displayed here as arrows impacting the direct causal effects of collective efficacy and police efficacy on crime.

I restate my hypotheses here, in the order they will be tested:

1. Police efficacy and collective efficacy moderate each others' effects on crime.
2. Police efficacy and collective efficacy are causally ordered. There are two components of this hypothesis:
   a. Police efficacy is an antecedent of collective efficacy. This may occur either slowly (lagged effects) or rapidly (simultaneous effect).
   b. Collective efficacy is an antecedent of police efficacy. This may occur either slowly

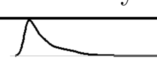
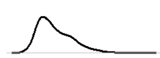
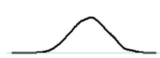
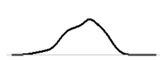
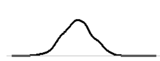
(lagged effect) or rapidly (simultaneous effect).

In the following sections, I briefly describe the data used to test these hypotheses, paying particular attention to measurement, then walk through the estimation approaches at length, discussing how they address potential violations of modeling assumptions.

3.2 Data and Measurement

This chapter uses a two-period neighborhood-level panel data set assembled from the 1995 Project on Human Development in Chicago Neighborhoods Community Survey (PHDCN-CS) (Earls et al. 1999) and the 2003 Chicago Community Adult Health Study (CCAHS) (House et al. 2011). These survey data are augmented with neighborhood measures constructed from indicators in the Longitudinal Tract Data Base (LTDB) (Logan, Xu, and Stults 2014) and police-reported crime from publicly accessible Chicago Police Department records (Chicago Police Department 2020). Because the data used here are identical to those used for Chapter 2, they are fully described in Appendix A to minimize redundancy. That appendix describes the data sources and details the measurement strategies which apply to both chapters. Table 3.1 depicts descriptive statistics for the measures used in this chapter. The following section details methods specific to this chapter.

Table 3.1: Descriptive statistics.

Measure	Mean	SD	Min	Density	Max
Homicide	2.03	2.39	0.00		15.00
Perceived Violence	0.00	1.00	-1.95		2.94
Victimization	0.00	1.00	-2.08		3.79
Violent Crime	0.00	1.00	-1.71		4.92
Collective Efficacy	0.00	1.00	-3.64		3.00
Police Efficacy	0.00	1.00	-3.18		3.19
Reciprocated Exchange	0.00	1.00	-3.61		4.41
Attachment	0.00	1.00	-2.91		2.73

Measure	Mean	SD	Min	Density	Max
Disadvantage	0.00	1.00	-2.24		3.86
Stability	0.00	1.00	-2.38		1.95
Hispanic/Immigrant	0.00	1.00	-2.45		2.63

I conceptualize police efficacy as a neighborhood-level capacity to call upon police to engage in social control in accordance with the expectations of residents. That is, a neighborhood with high police efficacy is one where residents believe the police are capable of combatting crime, will respond and investigate when called, and will treat both callers and suspects fairly and respectfully. This definition encompasses both effectiveness and legitimacy, which are commonly found to be distinct in research on policing procedures (Tyler 2006), though Sampson and Bartusch (1998) combined five measures capturing both effectiveness and legitimacy (as "police satisfaction") in their analysis of legal cynicism using the PHDCN-CS. The same scale was also used by Silver and Miller (2004). One prominent study combined indicators of police efficacy into a legal cynicism construct (Kirk and Matsuda 2011). As documented in Appendix D, I found evidence in support of separating police efficacy from legal cynicism and omitting legal cynicism from the overall analysis.

To construct a police efficacy scale, I begin with the five indicators used by Sampson and Bartusch (1998) and Silver and Miller (2004) which encompass responsiveness, effectiveness in maintaining order and controlling crime, and fair treatment of both victims and suspects (see Appendix A). To these prior measures, I add three indicators reflecting resident perceptions of change in police protection over the last 5 years, excessive use of force, and failure to patrol and respond to calls. All eight measures are used together as factor analysis suggests the indicators are not clearly separable into different effectiveness and legitimacy factors, though they are separable from the indicators of collective efficacy—informal social control expectations and cohesion and trust. The 2003 police efficacy measure constructed from the CCAHS includes only three measures which encompass effectiveness, responsiveness, and fairness. The police efficacy measures are moderately correlated across waves ($\rho = 0.37$), somewhat less so than collective efficacy ($\rho = 0.47$). In figures below, the police efficacy measures are labeled PE_A for 1995 and PE_B for 2003 to remind the reader they are constructed from different indicators.

The crime measures used are police-reported homicide, survey-reported perceived violence, survey-reported violent victimization, and violent crime. The violent crime measure is a composite of two different measures. In 2003 the measure is constructed from the sum of homicides, robberies, and aggravated assaults and batteries in 2003 divided by the year 2000 population. In 1995, I use the violent crime measure from the PHDCN-CS aggregate NC-level dataset from ICPSR (Earls et al. 1999).[2] The interwave correlation for the two violent crime measures is 0.61 which is higher than that for any of the other crime measures. It is, however, more strongly correlated with the other 1995 crime measures than the 2003 violent crime measure is with the other 2003 measures. Thus the 1995 violent crime measure should be viewed cautiously. Unfortunately, I have no alternative measure for 1995 violent crime as the PHDCN does not provide one and the Chicago Police Department only provides data from the year 2000 onward. The ICPSR release of the PHDCN-CS is also missing values for homicide and violent crime in 1995 for one neighborhood. This observation is dropped in random- and fixed-effects models but included via full-information maximum likelihood in structural equation models. Inclusion has no impact on estimates.

3.3 Methods and Results

I use three general estimation strategies to test my hypotheses. I use random- and fixed-effects panel models test Hypothesis 1: collective efficacy and police efficacy moderate each other's effects on crime. Before testing this moderation hypothesis, I use two specifications to evaluate conditional associations of collective efficacy and police efficacy with crime, both overall and within each panel year. Moderation is unlikely to be found if those conditional

[2] This measure is undocumented, so it is uncertain if it represents police-reported violent crime like the constructed 2003 measure or some other composite measure such as the one used by Sampson and Bartusch (1998). The 1995 violent crime measure is correlated approximately 0.89 with the sum of the standardized homicide, perceived violence, and victimization measures, which is the index construction method described by Sampson and Bartusch (1998). Performing the same operation on the 2003 data yields a correlation of 0.53 with the police-report based violent crime measure. I thus strongly suspect this is indeed the index from Sampson and Bartusch (1998).

associations are weak or absent—as appears to be the case in 2003.

Hypothesis 2, that police efficacy and collective efficacy are causally ordered, is tested using two forms of structural equations: cross-lagged panel models and a simultaneous effect instrumental variables model. These models allow evaluating the directionality of associations using temporal ordering and assumptions about conditional independence. Using both types of model helps address the possibility that causal effects operate at different rates: cross-lagged models assume an 8-year lagged effect while the instrumental variables model assume they operate over the short term. Both forms of structural equation relax the assumption of time-invariant parameters by permitting the effects of collective efficacy and police efficacy on crime to differ in 1995 and 2003.

3.3.1 Random- and Fixed-Effects Panel Models

The first estimation strategy uses random- and fixed-effects panel models to estimate the conditional direct effects of collective efficacy and police efficacy on crime and test for moderation of these effects. These models correspond to the arrows in Figure 3.2 from collective efficacy and police efficacy to crime and the labeled moderation pathways. For these models, I first describe the estimation approaches and model specifications before discussing results.

For all four outcomes—homicide, victimization, violent crime, and perceived violence—I use four estimation approaches, and, within each approach, either three or four different specifications. These models make the assumption collective efficacy and policy efficacy have independent simultaneous effects on crime and neither is a mediator for the others' effects. If, for instance, police efficacy influences crime and is in part the result of collective efficacy, including it in a model alongside collective efficacy will attenuate the estimated effect of collective efficacy on crime. This is conditioning on a post-treatment mediator—controlling, in effect, for a mechanism of the causal variable of interest. If this attenuation occurs, however, it suggests police efficacy is either a mediator for collective efficacy or, if not, the effect of collective efficacy on crime is partly spurious, and police efficacy is an omitted variable in past studies.

Random effects

The first estimation approach is a simple panel regression with random intercepts for neighborhoods. For homicide, this is a Poisson regression with a population exposure term for which the coefficient is fixed to 1.[3] For the other outcomes, this is a standard linear regression. Identification of treatment effects in this approach relies on strong ignorability given covariates—adjustment for anything causally antecedent to both crime and either collective efficacy or police efficacy (see Lanfear, Matsueda, and Beach 2020). This includes both time varying and time stable confounders. An implication of this assumption is that we must assume there is no effect of past crime on present crime except through included covariates. If there is a direct effect of past crime on present crime or one mediated by any omitted variable, it will bias estimates for collective efficacy and police efficacy, because past research strongly suggests they are influenced by crime (Sampson 2012; Sampson and Bartusch 1998).

Lag homicide

The second estimation approach partially relaxes the assumption that past crime does not predict present crime—either directly or via an omitted mediator—by using the lag homicide rate as a predictor. Due to the absence of 1990 measures for any other outcomes, homicide must be used for lagged crime across all specifications. Note that while this is a conventional dynamic panel estimator for the homicide outcome (Wooldridge 2010), it is not for the other outcomes.[4] Rather, I am making the assumption that homicide captures most or all effects of past crime regardless of the outcome under consideration. Auxiliary models predicting second wave crime outcomes suggest this is the case except for perceived violence, where 1995 perceived violence dominates homicide in predicting 2003 perceived violence. However, perceived violence in 1995 has no substantively or statistically significant relationship with 2003 collective efficacy or police efficacy, so it is possible it may not threaten identification. These models retain the random effects from the prior specification, except in the case of

[3]Respecifying this as a negative binomial model reveals no evidence of overdispersion.

[4]One might think of it as a dynamic panel model with unmodeled measurement error in the predictor.

violent crime where a standard linear model with heteroskedasticity and autocorrelation consistent standard errors is used due to is insufficient inter-neighborhood residual variation to stably estimate random effects.

Fixed effects

We can relax the assumption that there are no time-stable omitted confounders using unit fixed effects specifications. With a two-wave fixed effects specification, we are estimating the relationship between deviations from unit-level means of the regressors and outcomes. This specification produces two major limitations: efficiency and inability to model stability over time. Fixed effects specifications use an additional degree of freedom for every observation, resulting in larger standard errors. They also cannot model observations for which there was no change between time periods. This does not result in bias, but does diminish statistical power. This second limitation is particularly problematic for rare outcomes like homicide. In the present case, 111 of the 342 neighborhoods with homicide data experienced the same number of homicides in both waves, including 75 which experienced none in either wave.[5] Due to the large number of observations that would be dropped due to fixed effects, tests would be quite underpowered. Consequently, I do not model homicide using this specification. The other outcomes are modeled using the fixed-effects ordinary least squares regressions from the `fixest` R package (Bergé 2018) with heteroskedasticity and autocorrelation consistent standard errors from the `sandwich` package (Zeileis, Köll, and Graham 2020).

Unit fixed effects models make the assumptions that past treatments (1) do not influence current outcomes (except via included covariates) and (2) past outcomes do not influence treatment (Imai and Kim 2019). Chapter 2 of this dissertation suggests the first assumption is violated in the case of collective efficacy, as past collective efficacy may exert crime-controlling effects via the built environment. This is typically addressed using lagged treatment variables (Imai and Kim 2019), but these are not available in the present data. Chapter 2 indicates

[5]If homicide is specified as a rate, rather than count, it is possible to recover the non-zero values due to changing population size (denominator). I chose not to do this as I would still lose over a quarter of all neighborhoods.

these effects are modest in magnitude, however, and thus unlikely to induce notable bias (though this does not rule out other mechanisms). Canonical research on collective efficacy suggests the second assumption is also violated due to feedback effects of crime on collective efficacy (e.g., Sampson 2012). While this may result in some bias in estimates, research adjusting for feedback effects of crime finds similar results to models without this adjustment (e.g., Sampson 2012; Sampson and Raudenbush 1999). Later in this section I describe an approach based on Sampson and Raudenbush (1999) which attempts to adjust for potential feedback effects of crime on collective efficacy using instrumental variables.

Gaussian Markov random field

It is reasonable to expect that crime rates in one neighborhood may depend on what occurs in other nearby neighborhoods. Spatial dependence in general will bias estimates of standard errors, and some forms—interference—will also threaten identification of treatment effects such as for collective efficacy. Moran's I tests of residual spatial dependence indicate most of the random effects specifications exhibit spatial dependence (but generally not the fixed effects). To address spatial dependence, my next estimation approach uses generalized additive models (GAMs) with a Gaussian Markov random field (MRF) spatial smoother fit using R's `mgcv` package (Wood 2017). This approach models spatial dependence between observations using a spatial random effect assumed drawn from a normal distribution with a mean equal to the mean of neighboring unit random effects. In MRFs, the "Markov" signifies that observations are independent of all non-neighboring observations conditional on their neighbors—like a Markov chain, it is "memory-less" as any given state only depends on its immediate antecedents. This independence assumption is relatively weak in many applications and makes large sample estimation tractable. Consequently, GRMFs are one of the most common approaches to spatial statistical modeling (Rue and Held 2005).

Instrumental variables

The last approach uses reciprocated exchange and kinship and friendship ties as instruments for collective efficacy analogous to the approach of Sampson and Raudenbush (1999). Those authors used reciprocated exchange, kinship and friendship ties, and neighborhood attachment as instruments for the effect of collective efficacy on crime in cross-sectional simultaneous equations using the same 1995 data as the present study. There, they found reciprocal effects between collective efficacy and both homicide and robbery. The attachment to neighborhood measures are unavailable in the 2003 wave, so here I use only reciprocated exchange and ties. This specification makes the strong and untestable assumption that the only relationship that reciprocated exchange and friend and kinships ties have with crime are explained by collective efficacy or other included covariates (Morgan and Winship 2015). Fixed effects are retained in this approach except for homicide. Homicide is also transformed into the log of the homicide rate to facilitate using a conventional linear two-stage least squares estimator.

Random- and Fixed-Effects Specifications

All approaches above were fit with multiple model specifications both to test hypotheses and relax potentially violated assumptions. These specifications are a (1) base specification, (2) a year interaction, (3) a interaction of Collective Efficacy with Police Efficacy, and (4) and specifications 1 through 3 with a spline on disadvantage to adjust for residual nonlinearity.

The base specification predicts the given crime outcome with collective efficacy, police efficacy, and five controls—the three structural measures, population density, and a dummy distinguishing panel waves. This specification is suitable for establishing baseline conditional associations between collective efficacy and police efficacy and crime. Note that the fixed effects specifications retain the year dummy control variable to adjust for overall differences in outcomes across waves. As a result, these are two-way fixed effects (TWFE) specifications. Recent research on TWFE estimators suggest they are problematic for causal inference in data with multiple periods and binary treatments due to these estimators calculating treatment effects in relation to already-treated units and assigning negative weights to some cases (Imai & Kim 2020). While research is still developing in settings with continuous treatments, this literature suggests these are less of a concern in two-period settings. Further, the present models are completely insensitive to the presence of the year dummy variable.

A limitation of the base specification is that, by fixing parameters to be invariant across waves, it makes the assumption the effects collective efficacy and police efficacy (as well the controls) are identical across waves of the panel. This assumption may be violated for both artificial and natural reasons. First, the much smaller sample size for the CCAHS means the 2003 measures are less precise than the 1995 measures which may artificially attenuate estimates for the second wave. If this is the case, it is arguable whether relaxing parameter invariance is desirable. Forcing invariance might be seen as borrowing information across waves since the first wave is more precisely estimated. Additionally, for police efficacy, the indicators are different between waves and there are only three indicators in 2003 compared to eight in 1995. If this reduced set of indicators does not tap the same dimensions of the underlying construct, we would expect the factor to exhibit a different relationship with crime. Similarly, if fewer indicators translate into less precision, it may further attenuate estimates.

Second, we might expect an actual "natural" difference in parameters due to shift in the relative contribution of informal and formal social control actions to rates of crime. This may occur from an increased reliance on invoking police to solve problems across the time period under consideration (Harcourt 2001; Sharkey 2018), or shifts away from conventional informal social control into new formally-mediated means (Carr 2003; Carr 2012). The first alternate specification addresses the possibility of varying effects across waves with interaction terms between survey year and both collective efficacy and police efficacy (but not between collective efficacy and police efficacy).

The third specification includes an interaction term between collective efficacy and police efficacy to permit testing Hypothesis 1: Police efficacy and collective efficacy moderate one-another in their effects on crime. If residents are emboldened to engage in informal social control due to the belief they are supported by effective police, we would expect to see a negative interaction coefficient: At high levels of both collective efficacy and police efficacy, there is an additional crime control benefit. In contrast to my theoretical expectation, if the crime control benefits of higher collective efficacy or police efficacy come mainly when the other is low, we may instead see a positive interaction term: At high levels of both collective efficacy and police efficacy, crime is higher than an additive relationship would predict.

The fourth and final specification is used only in a subset of MRF GAM models. Analysis of model residuals from across all estimators and specifications reveals a nonlinear relationship between disadvantage and crime. These GAM models use a nonlinear transformation of disadvantage via a thin-plate regression spline to address the nonlinear correlation in the residuals (Wood 2017). Thin-plate splines map a predictor on to the outcome via a smooth function with curvature penalized to prevent overfitting. The spline improves model fit notably but appears inconsequential for estimates of collective efficacy and police efficacy and the particular spline shape here is not replicable with any conventional polynomial term of reasonable degree.[6] Consequently, the spline model results are presented for comparison, but no similar transformation was attempted in the other approaches. No other covariates appear to display a significant nonlinear association with any of the outcomes.

3.3.2 Random- and Fixed-Effects Results

Rather than walking through the results for every one of the many estimation approaches and specifications, I graphically display all point estimates of interest and provide a holistic interpretation. Estimates for controls are not presented as they are not substantively meaningful given that collective efficacy and police efficacy are likely mediators of their effects on crime. Figure 3.3 is a full-page illustration of the point estimates for every combination of estimation approach and model specification described above. The top section shows point estimates of the effects of collective efficacy and police efficacy for the base models. The center section shows point estimates for the year interaction models broken out into year-specific estimates. The bottom section shows results from the collective efficacy and police

[6] Significant fit improvement was indicated by greater than 6 point reductions in Bayesian Information Criteria values (Raftery 1995) and insignificant combined adjusted quantile tests (Gelman and Hill 2007).

efficacy interaction models where the displayed point estimates are the interaction terms between collective efficacy and police efficacy.

The tight groupings of point estimates indicate they are fairly insensitive to model specification, except when instrumenting collective efficacy using reciprocated exchange and kinship and friendship ties. Similarly, the consistent error bars indicate precision is not greatly affected by modeling decisions except in the case of the instrumental variables, and, to a lesser degree, fixed effects. The unstable and imprecise estimates for collective efficacy in the instrumental variable specification may be indicative of weak instruments (Bielby and Matsueda 1991).

For collective efficacy, the results indicate an overall modest negative effect on crime, though small and insignificant in the case of homicide. Importantly, this overall effect of collective efficacy appears to be the average of a stronger negative effect in 1995 and, except in the case of perceived violence, a null effect in 2003. This might result if collective efficacy is endogenous to resident perceptions of crime—survey respondents may be basing informal control expectations on perceived crime (Matsueda and Drakulich 2016). The instrumental variables approach which attempts to adjust for this possibility finds null effects and imprecise estimates for collective efficacy. This appears to be due to two factors: (1) collective efficacy effects are present mainly in 1995, and (2) the inclusion of police efficacy attenuates the conditional association of collective efficacy with crime and greatly reduces precision of the estimates in these models. Restricting the model to 1995 and omitting police efficacy results in replication of the collective efficacy effects seen by Sampson and Raudenbush (1999). Assuming the instruments for collective efficacy are relevant and valid, this may occur if police efficacy is a mediator for collective efficacy's effect on crime. If so, including police efficacy in a model of collective efficacy and crime results in included post-treatment variable bias.

For police efficacy, we see similar overall effects to collective efficacy: modest negative effects on crime and a null effect for homicide. Interestingly, introducing instrumental variables for collective efficacy results in a notable strengthening of the police efficacy estimate

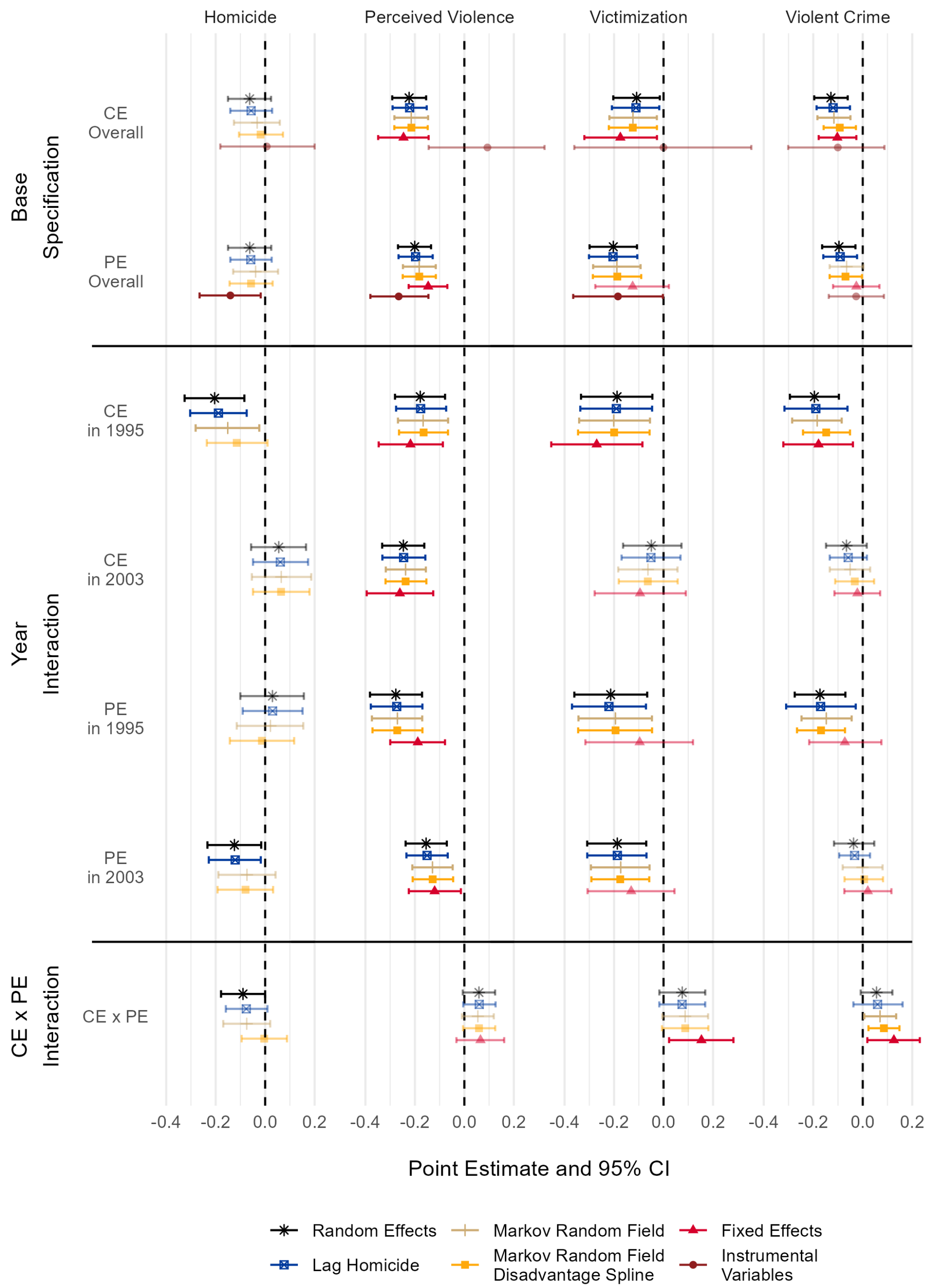


Figure 3.3: Estimated effects of collective efficacy and police efficacy on four forms of crime from six estimation strategies and four model specifications. Dots are point estimates. Bars are 95% confidence intervals. Estimates faded out where intervals include zero.

for perceived violence and homicide. In the year interaction specifications, we again see variation across waves in effects. For homicide, there is no observed police efficacy effect in 1995 and a weak negative effect in 2003, but there is the opposite pattern for violent crime. Perceived violence is relatively stable though stronger in 1995. Victimization is consistent across waves.

In the final pane, we see that the interaction between collective efficacy and police efficacy is, if present, modest in size. Most point estimates are positive, with the exception of homicide, but nearly all estimates are below the chosen threshold of significance. Positive moderation is more pronounced in the typically-conservative fixed-effects models, though this provides only weak evidence for moderation in light of the other estimates.

3.3.3 Causal Sequences

The next two sets of models are concerned with testing the causal ordering of collective efficacy and police efficacy. I use two strategies: a pair of cross-lagged panel models, which test causal effects between both collective efficacy and police efficacy over time using temporal ordering, and an instrumental variables model, which tests the contemporaneous causal effect of collective efficacy on police efficacy using strong assumptions about conditional independence.

Cross-lagged panel models

The first modeling approach for causal sequences evaluates the causal ordering between police efficacy and collective efficacy across time periods using cross-lagged panel models. As the primary focus here is not estimating effects on crime—though they are of some interest—I use only the two crime measures assumed to be most accurate: the log-rate of police-reported homicide and empirical Bayes estimates of survey-reported violent victimization. I estimate a system of structural equations with each crime measure. Figure 3.4 below depicts the homicide model graphically. In these equations, homicide (HOM) or victimization ($VICT$) is dependent on police efficacy (PE_A or PE_B), collective

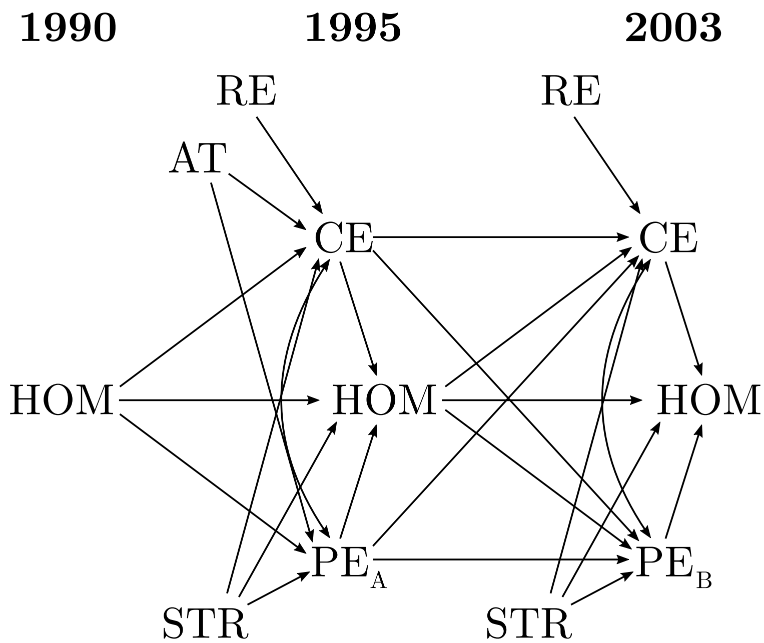


Figure 3.4: Two-wave cross-lagged model of collective efficacy, police efficacy, and homicide.

efficacy (CE), lagged crime, and the three structural neighborhood measures (STR). Collective efficacy and police efficacy depend on the lag of both measures, the lag of crime, and the three neighborhood structural measures of the most recent year. I also include contemporaneous residual correlations between collective efficacy and police efficacy in both time periods, signified by double-headed arrows. The structural models were estimated using bootstrapped standard errors and full-information maximum likelihood to address a single observation with missing values for 1990 and 1995 homicide.

For the equations with 1995 outcomes, I introduce reciprocated exchange (RE) as a predictor for contemporaneous collective efficacy, and attachment to neighborhood (AT) as a predictor for both collective efficacy and police efficacy. I omit kinship and friendship ties here as they are not significantly predictive of collective efficacy or police efficacy. There are sufficient degrees of freedom to test the independence restrictions featuring reciprocated exchange and attachment. Attachment is strongly related to both police efficacy and collective efficacy, and conditionally independent of crime. Reciprocated exchange is associated only with collective efficacy but may be related to 1995 victimization net of the other covariates (p = .049). The models are insensitive to removing these predictors or allowing them to directly predict victimization.[7] Only reciprocated exchange is available in 2003, and it is conditionally independent of victimization and homicide net of the other covariates.[8] The cross-lagged models are insensitive to excluding reciprocated exchange.

Under the assumption of strong ignorability given covariates, these cross-lagged equations allow estimating effects of collective efficacy and police efficacy on each other from 1995 to 2003. Importantly, however, the three structural measures for the 2003 wave are measured in 2000, after 1995 collective efficacy and police efficacy. This will attenuate their estimates if neighborhood sociodemographic characteristics act as a mediator for the intertemporal effects between collective efficacy and police efficacy. To address this, I specified alternate models with endogenous year 2000 structural variables—mediators for collective efficacy and police efficacy—and calculated the total intertemporal effects of police efficacy and collective efficacy as the sum of their direct effects plus the effects mediated by the structural variables. The alternate model produces nearly identical results to the primary models below.

Cross-lagged panel model results

Figure 3.5 depicts selected parameter estimates and standard errors from the two structural models. All estimates are standardized. The crime results roughly mirror those of the prior section. I find victimization is more consistently related to police efficacy, while collective efficacy is a stronger predictor of homicide, though only in 1995. Neither police efficacy nor collective efficacy significantly predict 2003 homicide. More importantly, these

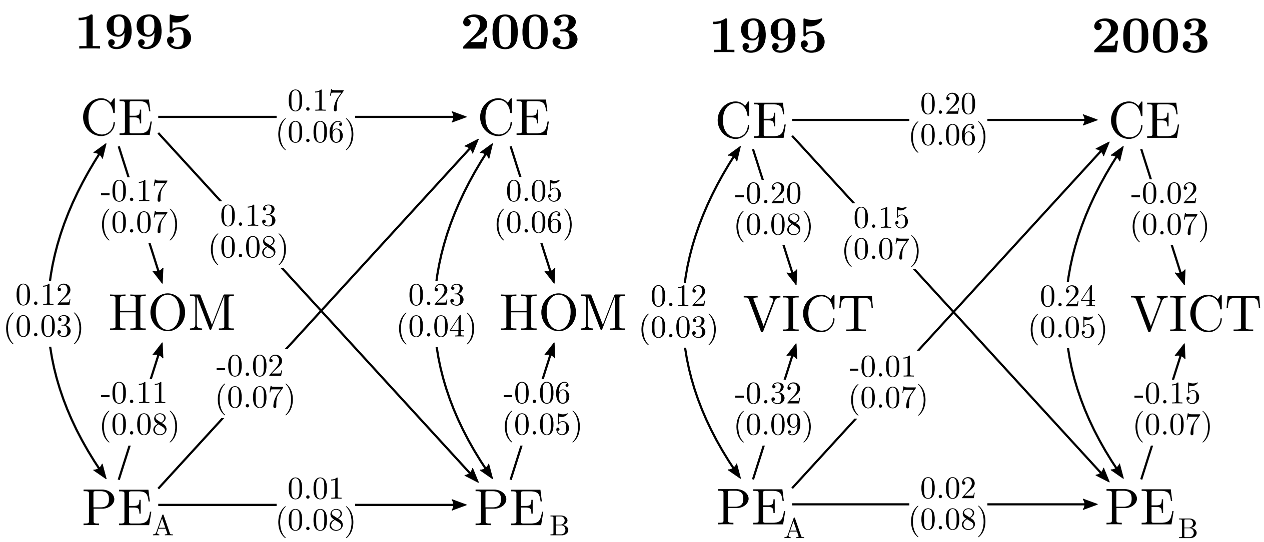
[7] These models feature 37 degrees of freedom due to four sets of restrictions: (1) enforcing temporal order (e.g., 2000 structural measures do not impact 1995 outcomes), (2) using only proximate predictors (e.g., 1990 structural measures do not impact 2003 outcomes net of 2000 structural measures), (3) assuming reciprocated exchange is conditionally independent of police efficacy and crime, and (4) assuming attachment is conditionally independent of crime. These restrictions improve interpretability and are theoretically justified—the models are also insensitive to relaxing restrictions 2 through 4.

[8] Note that finding conditional independence between reciprocated exchange and victimization or homicide is not indicative of a satisfied exclusion restriction to use reciprocated exchange as an instrument for collective efficacy's effect on crime. If there is confounding between collective efficacy and either crime outcome, the path from reciprocated exchange to crime is not identified, because collective efficacy is a collider on that path (Morgan and Winship 2015:301–2).

models allow us to see the intertemporal associations of these measures. Both systems of equations reveal a similar pattern: Police efficacy in 2003 is conditionally unrelated to 1995 police efficacy (despite a $\rho = .37$ bivariate relationship), but predicted by 1995 collective efficacy conditional on the structural covariates.[9] This indicates police efficacy is descended from collective efficacy, and thus may mediate its effects on crime. Effective policing may be a proximate determinate of victimization—evidence is weaker for homicide—but effective policing is in part the result of neighborhood collective efficacy. This is logical if collective efficacy captures resident propensity to report crimes or suspicious circumstances to police but responsiveness and effectiveness of law enforcement impacts crime—such as by further promoting calls to police or increasing the likelihood of apprehension.

These models exhibit relatively good fit, though better for victimization than homicide. The homicide model's Satorra-Bentler scaled Chi-square is significant ($p < .00$, $\chi^2 = 92.42$, $df = 37$) indicating overidentification restrictions in the model may not hold. Chi-square values increase in proportion to sample size, so rejection is common in even moderately-sized samples (Bollen 1989). Fit indices which adjust for sample size and/or model complexity provide better metrics for evaluating fit. The homicide model displays a Standardized Root Mean Square Residual (SRMR) of 0.020, Root Mean Square Error of Approximation (RMSEA) of 0.066 (90% CI: 0.049, 0.084), and Tucker-Lewis Index (TLI) of 0.934. Typical values indicating good fit are an SRMR below 0.080, RMSEA close to or below 0.060, and TLI close to or above 0.950 (Hu and Bentler 1999). The victimization model displays a significant Chi-square ($p = 0.03$, $\chi^2 = 55.14$, $df = 37$), an RMSEA of 0.038 (90% CI: 0.12, 0.058), SRMR of 0.018, and TLI of 0.971.

[9] In a simple standardized linear model predicting 2003 police efficacy with 1995 collective efficacy, introducing 1995 collective efficacy is sufficient to reduce the estimated cross-wave partial correlation of police efficacy from .37 to .19. Introducing disadvantage further reduces this to a statistically insignificant 0.07.



(a) Homicide

(b) Victimization

Figure 3.5: Selected estimates from cross-lagged panel models of collective efficacy, police efficacy, and police-reported homicide (a) or survey-reported victimization (b). Standard errors in parentheses. Control variables and pathways hidden for clarity. See Figure 3.4 for the full model.

Instrumental Variables Models

Cross-lagged models estimate the effects of collective efficacy and police efficacy on each other a relatively long span of time. Those models do not estimate their immediate effects on one-another, though they are permitted to exist with a contemporaneous error covariance at each time period. It is possible, however, that collective efficacy and police efficacy function as a sort of causal chain in a short time span. This section augments the cross-lagged model with instrumental variables to test the direct effect of collective efficacy on police efficacy in the short term while adjusting for the possibility of a reciprocal effect in the opposite direction.

Identifying causal effects in the presence of reciprocal feedback requires instrumental variables—variables which are relatively strongly correlated with the treatment of interest but impact the outcome only via the treatment or included covariates. With cross-sectional data, researchers typically use theory to locate and justify instruments. Sampson and Raudenbush (1999), for example, used attachment to neighborhood, friendship and kinship ties, and reciprocated exchange as instruments for the effect of collective efficacy on crime and disorder, based on the assumption they would only impact crime and disorder via collective efficacy. In the present case, we are interested in the effects of collective efficacy and police efficacy on one-another. I am aware of no available instruments for police efficacy which are plausibly independent of collective efficacy.

When repeated observations are available, researchers may instead turn to lags of the endogenous variables as instruments under the assumption there are no cross-lagged effects—the instrument must be valid. A requirement of this approach, however, is that there is a strong association between observations of the same variable over time—the instrument must be relevant. Results of the prior section indicate a cross-lagged effect of collective efficacy on police efficacy and a strong intertemporal association within collective efficacy. If this cross-lagged effect is actually zero in the population and reflects only a true contemporaneous association, the instrument may be relevant and valid. Police efficacy does not, however, display any significant intertemporal relationship with itself conditional on the structural covariates (again, despite a $\rho = .37$ unconditional association). This means past police efficacy is unsuitable for use as an instrument for present police efficacy (Wooldridge 2003:493).

Consequently, lacking any valid or relevant instruments for police efficacy, estimation of simultaneous causal effects is limited to a unidirectional instrumental variables model of the effect of collective efficacy on police efficacy. I instrument the effect of collective efficacy on police efficacy using reciprocated exchange in 1995, and both reciprocated exchange and past collective efficacy in 2003. This cannot, of course, rule out the possibility that there is a contemporaneous effect of police efficacy on collective efficacy, but it provides evidence against assumptions that collective efficacy is purely descended from police efficacy. Because our focus here is only on the effect of collective efficacy on police efficacy, I do not model homicide or victimization as outcomes. Rather, lagged homicide is included to block potential cross-lagged effects from collective efficacy to police efficacy. Results are insensitive to excluding homicide. As before, police efficacy and collective efficacy in each time period are modeled as dependent on the structural neighborhood measures. Figure 3.6 depicts the full instrumental variable model. Exogenous variables are permitted to covary, otherwise absent arrows indicate model restrictions.

I include attachment to the neighborhood in the equations for the first wave to block potential paths from reciprocated exchange to police efficacy via attachment. Silver and Miller (2004:573–74) noted the possibility that attachment may be descended from collective efficacy if residents become more attached to their neighborhood when they perceive their neighbors to be committed to regulating deviance. In this specification, even if reciprocated exchange or police efficacy impact attachment, the path from collective efficacy to police efficacy is identified. The estimated effects of collective efficacy on police efficacy are robust to the omission of attachment in the first wave. Attachment is not available in the 2003 wave. It is possible this may compromise the validity of the reciprocated exchange instrument by opening backdoor path to police efficacy. An auxiliary model using only 1995 collective efficacy as an instrument for 2003 collective efficacy produces similar results though with less precision.

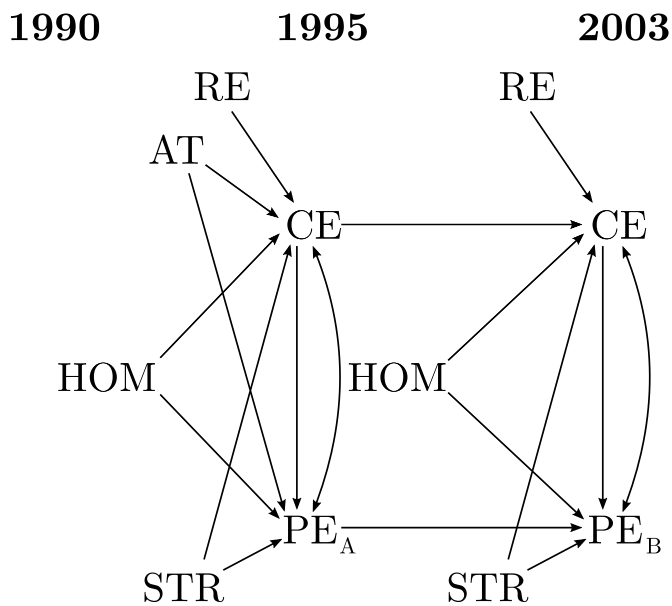


Figure 3.6: Two-period instrumental variable model of police efficacy and collective efficacy. All covariances between exogenous variables are unrestricted.

An additional illustration may clarify assumptions in the model. If we consider only the equations for the first wave of the instrumental variables model and simplify to the relevant elements of the model, we arrive at the directed cyclic graph in Figure 3.7. Our interest is in path a from collective efficacy to police efficacy. Estimation of this is complicated because the reverse causal path, b, may exist, and there may also be omitted variables, U, confounding estimation of these pathways. While depicted as a confounder here, the causal role of attachment (AT) is also ambiguous. It may precede both collective efficacy and police efficacy as shown, or, perhaps it precedes collective efficacy but is descended from police efficacy. Similarly, it may either precede or be preceded by reciprocated exchange (RE). Regardless of which case is true, path a is still identified using reciprocated exchange as an instrument, under the assumption reciprocated exchange has no impact on police efficacy or its unmeasured antecedents net of included variables (i.e. path c is zero).

Using past collective efficacy and police efficacy as instruments makes the strong assumption that the cross-lagged effects seen in the prior section are actually zero conditional

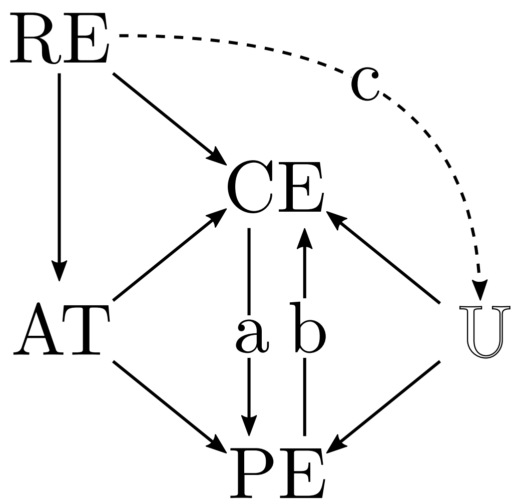


Figure 3.7: Directed graph of reciprocal relationship between collective efficacy and police efficacy with reciprocated exchange and attachment.

on their contemporaneous reciprocal effects. Fortunately, the reciprocated exchange instruments for collective efficacy are sufficient to identify the contemporaneous reciprocal effects while relaxing the restrictions on the cross-lagged effects. I found support for the restricted specification: Conditional on the associations in 2003, there are no substantively or statistically significant cross-lagged effects, and a Chi-square test between the restricted and unrestricted models is not significant. Note that this is not a test of the exclusion restriction for use of 1995 collective efficacy as an instrument for the effect of 2003 collective efficacy on police efficacy. In the presence of a reciprocal effect or confounding between collective efficacy and police efficacy in 2003, the cross-lagged path from 1995 collective efficacy to 2003 police efficacy is not identified. This test merely indicates the results do not rely on making the assumption of an absence of cross-lagged effects.

Instrumental variables model results

Figure 3.8 displays selected results from the instrumental variables model (see Figure 3.6 for the full model). The key results seen here mirror those of the cross-lagged models in the prior section: Collective efficacy has a strong effect on police efficacy. As before, police efficacy displays no significant intertemporal relationship with itself conditional on collective efficacy and neighborhood sociodemographic structure. In contrast, collective efficacy exhibits inherent stability over time. These results provide evidence for the hypothesis that collective efficacy precedes police efficacy. Further, this suggests models which attempt to estimate the effect of collective efficacy on crime may be misspecified if they include police efficacy without estimating the indirect (mediated) effect of collective efficacy via police efficacy. This model cannot, however, rule out the existence of a simultaneous reciprocal path from police efficacy back to collective efficacy. The residual covariance between police efficacy and collective efficacy in both time periods is, however, substantively and statistically weak. Overall, this model fits well. Its Satorra-Bentler Chi-square is significant ($p = .011$, $\chi^2 = 42.70$, $df = 24$[10]) but it displays a RMSEA of 0.048 (90% CI: 0.023, 0.071), SRMR of 0.012, and TLI of 0.978.

3.4 Discussion

The goal of this chapter is to evaluate the effects of collective efficacy and police efficacy on each other and on crime. Based on my own theoretical framework and the existing literature, I proposed two hypotheses: (1) collective efficacy and police efficacy have an interactive (moderated) effect on crime, and (2) collective efficacy and police efficacy are links in a causal chain. With regard to the first hypothesis, results from random- and fixed-effects panel models produce weak evidence for the moderation hypothesis. Estimates for the interaction terms are positive for perceived violence, victimization, and violent crime, but negative for homicide. In most cases these estimates not statistically distinguishable from zero, though the conservative fixed effects estimator indicates a positive effect for victimization and violent crime.

[10] The restrictions on this model (which can be seen in Figure 3.6) stem from (1) the identification restrictions (e.g., reciprocated exchange is conditionally independent of police efficacy), (2) using only the immediately preceding crime and structural measures to predict collective efficacy and police efficacy (e.g., 1990 disadvantage to predict 1995 collective efficacy, but not 2003 collective efficacy), and assuming no cross-lagged effects between collective efficacy and police efficacy.

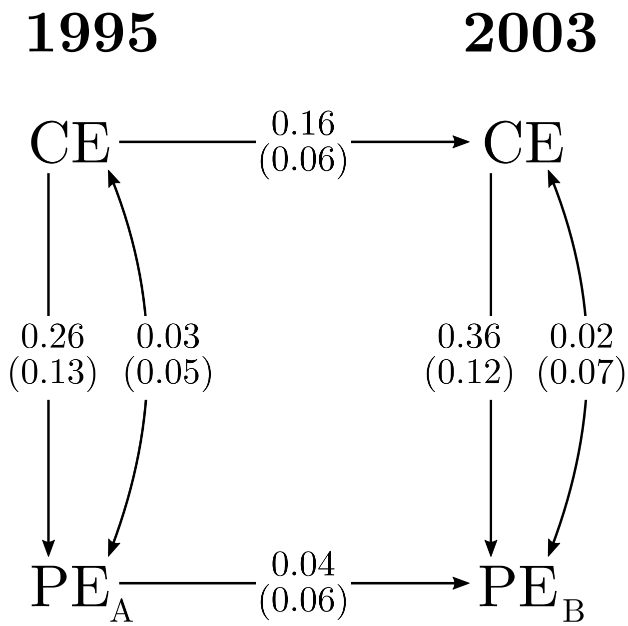


Figure 3.8: Selected estimates from instrumental variables panel model of the contemporaneous effect of collective efficacy on police efficacy.

The weak evidence for moderation may in part be the result of the unexpectedly weak effects of collective efficacy in the 2003 period, which are at odds with much of the research in this area (Lanfear, Matsueda, and Beach 2020). The cause of this difference from the canonical 1995 results is unknown, as the data were collected in the same city, using the same survey instruments, and relatively soon after the 1995 PHDCN-CS. It is not possible to discern if this is an artifact of measurement or sampling variability. For instance, the smaller sample size of the 2003 CCAHS results in less reliable estimates of collective efficacy and police efficacy, which may in turn inflate standard errors.

Differences across time periods may also reflect actual changes in Chicago, such as a shift away from reliance on informal control or an overall decrease in serious violence which reduces variation, resulting in less statistical power to detect relationships. It may also indicate some omitted factors outside both collective efficacy and police efficacy became more consequential in the later period. Local organizations, such as non-profits focused on community-building, have been suggested as an underappreciated source of crime control effects (Sharkey, Torrats-

Espinosa, and Takyar 2017), but research in this area implies these effects should operate through collective efficacy (Morenoff, Sampson, and Raudenbush 2001). More longitudinal neighborhood studies of collective efficacy are warranted, particularly with additional waves of existing datasets, and researchers should be attentive to the possibility that effects vary across time periods. Both quantitative and qualitative research designs should also be used to investigate the possibility that means or effects of neighborhood social control are shifting over time.

With regard to Hypothesis 2, in contrast to the causal order assumed in some prior research—sometimes using the same data as this analysis—police efficacy appears to be descended from collective efficacy. Police efficacy exerts no statistically significant influence on collective efficacy over the eight-year gap between panels in cross-lagged models. In both cross-lagged models of intertemporal effects and instrumental variables models of immediate effects, collective efficacy exerts a strong effect on police efficacy. Further, police efficacy does not appear to have any intrinsic stability over time independent of collective efficacy and neighborhood structure–virtually the entire bivariate correlation between the two police efficacy measures ($\rho = .37$) is eliminated by adjusting for collective efficacy, disadvantage, and, to a lesser degree, stability. It is possible this lack of interwave stability is in part related to using different indicators in each wave, however the police efficacy measures exhibit similar associations with other measures within each wave.

Future studies of neighborhood social control should carefully consider how models may be sensitive to assumptions about causal ordering. If police efficacy is causally descended from collective efficacy, research on collective efficacy and crime which controls for perceptions of police effectiveness and legitimacy may be inadvertently controlling for a post-treatment mediator, attenuating effects of collective efficacy on crime. This means results in which police efficacy appears to attenuate or dominate collective efficacy's effects on crime—as seen in the random- and fixed-effects models—may be misleading. Similarly, models featuring perceptions of police as a predictor of collective efficacy may be misspecified.

This causal ordering is plausible if most policing is reactive and collective efficacy captures in part the propensity of neighborhood residents to engage in monitoring and reporting of crime. This may result in more effective policing. An important implication of this, however, is that if exogenous factors depress perceived effectiveness and legitimacy of the police, it may result in higher crime overall by disrupting one of the pathways linking collective efficacy to crime. Police bias and misconduct, for instance, may reduce willingness to call police due to concerns over the potential consequences of calling. Perceptions of these consequences are important given how often that potential is realized as a fatal outcome, particularly for black subjects (Edwards, Esposito, and Lee 2018). For example, evidence indicates favorability toward police decreased precipitously across the United States following the murder of George Floyd by police officers in May 2020 and the resulting nationwide protests (Reny and Newman Forthcoming). In this way police bias and misconduct may undermine crime control functions of law enforcement. This is not a novel conclusion, but rather a small addition to the expansive literature drawing similar conclusions from different approaches and bases of evidence (National Research Council 2004; e.g., Tyler and Huo 2002; Wood, Tyler, and Papachristos 2020).

Future research should attempt to replicate the finding that collective efficacy precedes perceptions of police effectiveness and legitimacy, as well as investigate mechanisms for this relationship. Testing this effect convincingly is challenging as collective efficacy is difficult to manipulate experimentally and studies based on observational data—such as this one—rely on strong modeling assumptions. If this finding is robust, however, it may have an important implication for policy: interventions which increase police effectiveness and legitimacy may not increase collective efficacy—or perhaps may do so only indirectly via effects on crime and other neighborhood conditions. Regardless, of course, increasing the effectiveness and, in particular, fairness of policing would remain an important goals for both intrinsic reasons and reductions in crime and the harmful consequences of police-citizen encounters.

While beyond the scope of the present work, police efficacy may also affect the types of incidents in which residents will intervene and the form those interventions will take. For example, if residents believe police are highly effective but informal control is unlikely to be effective, they may invoke law enforcement to resolve minor incidents they would otherwise ignore or respond to informally (e.g. Schneider, Burcart, and Wilson 1976). This may be the case in neighborhoods with high police efficacy but weak informal social control, such as gentrifying neighborhoods with destabilized ties, as suggested by Kreager, Lyons, and Hays (2011:635) and (Lanfear, Beach, and Thomas 2018). Similarly, when calling the police is perceived as an inappropriate intervention for a situation—due to the possibility for violence or legal consequences—the ability to invoke other actors may affect both the decision to intervene and the ultimate outcome of interventions. Alternatives to invoking police, like community responder models, might reduce the relevance of police efficacy for disorder and crime control while improving outcomes for contacted individuals, particularly in terms of safety (Irwin and Pearl 2020). Future studies should examine how collective efficacy, police efficacy, and alternate means of intervention relate to both the type of situations in which residents intervene and the means by which they make those interventions.

In summary, this work attempts to identify how police efficacy—resident perceptions of police effectiveness and legitimacy—relates to collective efficacy and neighborhood crime rates. I examined first whether collective efficacy and police efficacy increase the effects of one-another on crime using longitudinal data in with variety of model specifications and estimators. I find weak evidence for a positive interaction. I then used cross-lagged panel models and instrumental variables to attempt to determine how police efficacy and collective efficacy are causally related. My results consistently indicate police efficacy is descended from collective efficacy, in contrast to a prominent literature that assumes the opposite causal relationship, that police efficacy promotes collective efficacy. This has important implications for future research as well as policy. Studies that treat collective efficacy as a mediator for police efficacy may produce biased and misleading estimates. Similarly, interventions that attempt to bolster collective efficacy by promoting perceptions of police efficacy may be unlikely to yield the intended results.

CONCLUSION

This dissertation proposes an integrated multi-level theory of social structure and criminal opportunity. It also presents empirical tests of two sets of propositions related to this multi-level theory. In this closing chapter, I first review the key findings and implications of each chapter of the dissertation, then discuss future directions for research suggested by my theoretical framework and empirical results.

3.5 Contributions

Chapter 1 presents a detailed overview of key social structural explanations of crime and proposes an integrative theory based on situational social interaction. The primary contribution of this chapter is the specification of social mechanisms for these structural theories, which are presently underdeveloped. The proposed micro, micro-macro, and macro-micro mechanisms generate testable propositions to guide future macro- and multi-level research on neighborhood crime. The interactional social mechanisms present a secondary contribution by connecting collective efficacy, broken windows, and routine activities to cultural explanations of violence, situational models of crime, and perception and interpretation of disorder and crime.

Chapter 2 proposes the built environment as a mechanism by which collective efficacy reduces crime, and presents an empirical test using block-level built environment data nested in Chicago neighborhoods. Results indicate collective efficacy negatively predicts built environment features like abandoned buildings and mixed land use, which, in turn, positively predict violence and property crime. This chapter makes two main contributions. First, it provides evidence for a macro-micro mechanism by which collective efficacy reduces incidents of crime. While evidence for the effect of collective efficacy on crime is relatively strong at the neighborhood level, the commonly proposed mechanisms that translate collective efficacy into fewer incidents of crime—such as informal control—are largely unobserved. Control of the built environment is a mechanism strongly support by research linking built environment features to criminal opportunity. These findings thus provide an observable mechanism for collective efficacy while linking it into the broad situational opportunity literature. Second, this chapter implicates collective efficacy in promoting the stratification of neighborhoods in physical quality. The built environment is an important predictor of the quality of life and wellbeing of residents. High collective efficacy may enable neighborhoods to accumulate beneficial features, while low collective efficacy neighborhoods accumulate harmful features that they lack the power to resist or remove. Thus, collective efficacy may promote neighborhood inequality by influencing the allocation of resources and development.

Chapter 3 contributes to the literature on policing and collective efficacy by testing a strong and commonly-made assumption—that police efficacy promotes collective efficacy. It also proposes an alternative hypothesis: police efficacy strengthens the effect of collective efficacy on crime. This chapter tests these propositions using two waves of community survey data from Chicago in a variety of model specifications. In contrast to the existing literature, the results provide consistent evidence that police efficacy is descended from collective efficacy. Mixed evidence is found for the moderation hypothesis. The findings from this chapter have important implications for future research as well as policy. Studies that treat collective efficacy as a mediator for police efficacy may produce biased and misleading estimates. Similarly, interventions that attempt to bolster collective efficacy by promoting perceptions of police efficacy may be unlikely to yield the intended results. Additionally, protective effects of collective efficacy may be interrupted when exogenous factors suppress actual or perceived effectiveness and legitimacy of police.

3.6 Future Directions

The first clear directions for future research are stronger and more comprehensive tests of collective efficacy and its mechanisms. The empirical chapters of this dissertation found weak effects of collective efficacy on crime. As our recent review concluded (Lanfear, Matsueda, and Beach 2020), stronger tests of the effect of collective efficacy on crime are needed, in particular using longitudinal data and causal designs. Particular attention should be paid to uncovering causal mechanisms for collective efficacy—in particular actual methods of intervention. This could be accomplished by augmenting surveys with vignettes probing means of intervention or conducting field experiments that hold constant deviance and attempt to induce sanctions in neighborhoods varying in collective efficacy. An important question this research might answer is, how do the means of intervention differ across neighborhoods varying in collective efficacy—and possibly more importantly—economic advantage and racial composition? It is likely the mechanisms that translate collective efficacy into low crime vary across neighborhoods, such as in the use of mediating actors, a point I return to shortly.

The results of Chapter 2 suggest the need for a deeper examination of the link between collective efficacy and the built environment. The built environment structures all human activity and consequently has wide-ranging impacts on individual and collective wellbeing. Collective efficacy may facilitate neighborhood stratification by impacting the ability of communities to attract, maintain, and compete for features of the environment that promote wellbeing. It is important that we understand how this occurs and what effects it has on neighborhoods and cities. This thread of research should consider the physical development of land over time as the result of a complex multi-level system relating local factors like crime, neighborhood wellbeing, the actions of residents—actions which include not just interventions but also residential mobility—and broad metro- and region-wide processes (e.g., Dreier, Mollenkopf, and Swanstrom 2014; Logan and Molotch 2007). This calls for situating collective efficacy in a broader political economy framework, a worthwhile long-term goal for theoretical development in this area.

The results of Chapter 3 call into question assumptions made about the role of police effectiveness and legitimacy in the neighborhood social control system: collective efficacy does not appear to be influenced by police efficacy. These findings suggest new directions for research. First, the causal ordering of collective efficacy and police efficacy has important implications for research and policy. Consequently, these results should be replicated in other settings and samples, ideally newly collected data, as the social context of policing has changed since the data used in this dissertation were collected. Second, the mechanisms linking collective efficacy to police efficacy are only speculative (e.g., more frequent resident interventions make policing fairer and more effective). Researchers should attempt to identify the mechanism in operation. This is likely to require collection of new survey data or interviews embedded in neighborhoods varying in collective efficacy and police efficacy. Third, both empirical research and theory on collective efficacy would benefit from disentangling formal social control from informal social control. While collective efficacy may capture a general capacity for intervention by residents, the consequences of these forms of intervention—as well as the factors influencing their relative use—are categorically different.

Both empirical chapters propose mechanisms for collective efficacy which require operating through mediating actors and organizations such as police and local government. This suggests theoretical extensions to collective efficacy—a focus on these mediating actors—and new directions for empirical research. Future research should interrogate the role of these actors in facilitating—or impeding—resident actions to address crime and perceived opportunities. The full range of actors and organizations efficacious residents engage to address different classes of problems is presently unknown. Einstein, Glick, and Palmer (2020) found residents were remarkably resourceful in efforts to combat developments like low income housing. It is reasonable to expect residents are similarly innovative in addressing crime and other social problems. Previously unconsidered means of intervention might provide mechanisms explaining collective efficacy's broad effects on community wellbeing. We may also consider how changes in available means–new mediating actors—might alter resident behavior and outcomes such as crime and the built environment. For example, the availability of non-police responses—like community responder models Irwin and Pearl (2020)—might encourage resident interventions when invoking police is perceived as excessive or dangerous.

A related concern is how interventions that operate through these mediated actors and organizations impact individuals, neighborhoods, and cities. Broad literatures document the consequences of residents invoking police, which results in racial disparities in contacts and use of force, or influencing the built environment, which extends and maintains racial-residential segregation. As research uncovers new mechanisms for collective efficacy that operate through mediating actors, researchers must consider how the actions of those actors result in inequitable or harmful outcomes. Wilson and Kelling (1982:6) asked, if we empower police to respond as residents desire, "How do we ensure, in short, that the police do not become the agents of neighborhood bigotry?" Similarly, we must ask how representatives and agencies of local government can be responsive to residents without acting to "maintain the racial or ethnic purity of a neighborhood," (Wilson and Kelling 1982:6). This area of research is important for connecting collective efficacy to the broad literatures on political economy and urban inequality.

Just as the empirical chapters argue for extending collective efficacy upward to systems and processes operating at the level of the city, the theoretical chapter argues that future research should extend collective efficacy—and other social structural theories of crime—downward to individuals and the situation. While collective efficacy has been linked to many indicators of community wellbeing, there is presently no coherent framework that explains why these effects exist or where to expect to find similar effects. This is because most of the outcomes of interest in this literature manifest at the level of individuals or situations, but collective efficacy focuses on macro-level relationships with no clearly elaborated micro- or cross-level mechanisms. Collective efficacy theory tells us what to expect at the macro-level but does not explain why: it is a black box. Opening this black box is necessary for producing a complete explanation of how collective efficacy reduces crime—and, as this dissertation discussed, influences the built environment and effective policing. It is also important for determining how to manipulate collective efficacy, whether for policy or research, and address possible negative consequences (e.g., Lyons 2007). Specification of mechanisms also facilitates linking collective efficacy to other social structural theories that imply similar micro-mechanisms (e.g., broken windows).

The first chapter of this dissertation is an initial effort at extending collective efficacy to the situation and integrating it to other theories of neighborhood social structure. The next steps for this effort are refining the theory and generating and testing propositions empirically. As with the suggestion to extend collective efficacy into a broad political economy framework, articulating a multi-level theory of the situation is a long-term, but worthwhile, goal.

3.7 Coda

It is my hope this volume stimulates deeper thinking about neighborhood-level explanations for crime. The goal of this work is not to unnecessarily complicate collective efficacy theory—or broken windows, or routine activities—but rather to clarify. Clearly-specified theories with explicit mechanisms permit more convincing tests and accurate predictions. They also allow us to recognize similarities between disparate frameworks, bridging seemingly conflicting perspectives to develop more complete and satisfying explanations. Finally, understanding the social mechanisms that produce collective efficacy and translate it into neighborhood safety and wellbeing will imply interventions to improve conditions in the most disadvantaged neighborhoods–which should be the ultimate goal of neighborhood research.

Appendix A

DATA AND MEASUREMENT OVERVIEW

This appendix provides an overview of all data used in this dissertation as well as approaches used to derive composite measures from indicators (e.g., multilevel measurement models).

A.1 Neighborhood Structural Measures

The social disorganization tradition recognizes crime and social control are rooted in structural characteristics of neighborhoods. To construct these measures, I obtained nine decennial census measures from the Longitudinal Tract Data Base (LTDB) (Logan, Xu, and Stults 2014) based on those used by Sampson, Raudenbush, and Earls (1997). The LTDB reweights indicators across changing boundaries between the 1990 and 2000 censuses to ensure they describe the same geographic areas. All measures are percentages and are listed in A.1. I use an oblimin-rotated alpha-scoring factor analysis to perform dimension reduction on these measures (Kaiser and Caffrey 1965). The factors were calculated simultaneously using both 1990 and 2001 observations for each NC to generate comparable measures over time. Three factors explain 87% of variation in the nine indicators and exhibit acceptable model fit ($\chi^2 = 7.69$, $df = 12$, $p = 0.81$). Loadings are depicted in A.1.

Table A.1: Factor loadings for neighborhood structural measures.

Measure	Disadvantage	Hispanic / Immigration	Stability
Under 18	1.03	0.25	-0.13
Unemployment	0.74	-0.33	0.14
Poverty	0.69	-0.15	0.43
Female-Headed Households	0.67	-0.44	0.27
Home Ownership	-0.09	0.02	-0.96
Moved in Last 10 Years	-0.19	0.34	0.79
Hispanic	0.30	0.93	0.05
Foreign Born	-0.12	0.83	0.15
Non-Hispanic Black	0.43	-0.71	-0.03
Eigenvalue	3.15	2.74	1.98
Proportion of Variance Explained	0.35	0.3	0.22

Based on the indicators which most highly load on each factor, they are described as disadvantage, Hispanic / immigrant, and stability. Disadvantage loads primarily on under-18 population, unemployment, poverty, and female-headed households, and to a lesser-degree non-Hispanic black population. Hispanic / immigrant loads on Hispanic population, foreign born, and negatively on non-Hispanic black. Stability loads negatively on home ownership and positively on moves in the last 10 years. These were extracted as neighborhood-level correlation-preserving factor scores to produce a parsimonious set of structural predictors for use in subsequent models (ten Berge et al. 1999).

While the measures were chosen to replicate the structural measures used in Sampson, Raudenbush, and Earls (1997), one indicator for disadvantage—percent of families on public assistance—was not available in the LTDB. The indicator for recent moves is also in the last 10 years rather than 5 years. Even with these differences—and calculating across both waves simultaneously—the resultant factor scores for 1990 neighborhoods are all correlated at over

$\rho = .95$ with those from Sampson, Raudenbush, and Earls (1997).[1]

A.2 Neighborhood Social and Perceptual Measures

The neighborhood social and perceptual measures were calculated using multi-level measurement models which adjust for sociodemographic composition of neighborhoods and conservatively shrink estimates toward zero where interrater reliability is lower (Sampson, Raudenbush, and Earls 1997). These measures include collective efficacy, police efficacy, perceived violence, legal cynicism, violent victimization, and local ties and exchange. Violent victimization is a single binary indicator estimated with a logistic regression while the remaining measures feature multiple four- or five-category ordinal indicators estimated using linear regression. Multiple-indicator measures include dummies for each indicator to adjust for item difficulty and random respondent intercepts. All models feature neighborhood-level random intercepts which are extracted and used as in subsequent models as empirical Bayes estimates of the neighborhood measures. I use a single factor for Collective Efficacy which combines Cohesion and Trust and Informal Control Expectations to mimic existing work in this field and using these data. A two-factor solution is preferred in confirmatory factor models, though the resulting separate factors are highly correlated at both the individual ($\rho = 0.70$ in 1995, $\rho = 0.67$ in 2003) and neighborhood level ($\rho = 0.71$ in 1995, $\rho = 0.64$ in 2003).[2]

A.2 depicts all indicators used to calculate the neighborhood measures including loadings from confirmatory factor analyses and overall neighborhood-level measure reliability from each multilevel model. Bracketed loadings reflect loadings on separate Cohesion and Trust and Informal Control Expectations factors for comparison to the combined Collective Efficacy Factor. For measures with two indicators like friend and kinship ties, a polychoric correlation between the indicators is reported in parentheses instead of item loadings. Note

---

[1] Another benefit of recalculating these factors is that the PHDCN-CS data has missing values on all neighborhood measures for one NC (749). Calculating new scores thus recovers one missing observation.

[2] I could potentially fit alternate models using an interaction between the separate factors but it wouldn't give any leverage on any questions I am interested in.

some measures differ between the 1995 and 2003 surveys, in particular, the indicators for police efficacy. Dashes indicate missing indicators for a given survey.

Table A.2: Loadings and reliabilities for neighborhood perceptual measures.

Measure / Indicator	Loadings / Reliabilites (A) PHDCN (1995)	CCAHS (2003)
Collective Efficacy (Cohesion & Trust + Informal Control Expectations)	A=0.758	A=0.503
Cohesion & Trust (”How much do you agree that…”)	A=0.763	A=0.453
People around here are willing to help their neighbors.	0.699 [0.766]	0.775 [0.813]
People in this neighborhood can be trusted.	0.726 [0.795]	0.824 [0.881]
This is a close-knit neighborhood.	0.660 [0.707]	0.624 [0.646]
People in this neighborhood generally… get along with each other.	0.515 [0.558]	0.752 [0.799]
People in the neighborhood… share the same values.	0.483 [0.521]	0.751 [0.790]
Informal Control Expectations (”How likely is it…”)	A=0.705	A=0.469
If a group of neighborhood children were skipping school and hanging out on a street corner, how likely is it that your neighbors would do something about it?	0.708 [0.788]	0.652 [0.780]
If some children were spray-painting graffiti on a local building, how likely is it that your neighbors would do something about it?	0.792 [0.874]	0.677 [0.811]
If a child was showing disrespect to an adult, how likely is it that people in your neighborhood would scold that child?	0.629 [0.705]	0.593 [0.689]
If children were fighting out in the street, how likely is it that people in your neighborhood would stop it?	0.623 [0.681]	0.556 [0.644]
Neighborhood residents would organize to keep closest fire station open if it were to be closed down by city because of budget cuts.	0.615 [0.652]	0.578 [0.653]
Police Efficacy & Legitimacy	A=0.808	A=0.422
Police in the neighborhood are responsive to local issues. (Strongly Agree to Strongly Disagree)	0.787	-
Police are doing a good job in dealing with problems that really concern people in the neighborhood. (Strongly Agree to Strongly Disagree)	0.863	-

Measure / Indicator	Loadings / Reliabilites (A) PHDCN (1995)	CCAHS (2003)
Police are… doing a good job in preventing crime in the neighborhood. (Strongly Agree to Strongly Disagree)	0.597	-
Police do a good job in responding to people in the neighborhood after being victims of crime. (Strongly Agree to Strongly Disagree)	0.584	-
Police are… able to maintain order on streets and sidewalks in the neighborhood. (Strongly Agree to Strongly Disagree)	0.585	-
In the past five years the level of police protection has gotten… (Better to Worse)	0.576	-
How much of a problem is police not patrolling the area or responding to calls from the area? (Major Problem to Not a Problem)	0.792	-
How much of a problem is excessive use of force by police? (Major Problem to Not a Problem)	0.654	-
How good a job are the police doing in working together with residents in your neighborhood to solve local problems? (Good to Poor)	-	0.745
The police are fair to all people regardless of their background. (Strongly Agree to Strongly Disagree)	-	0.704
The police in your local community can be trusted. (Strongly Agree to Strongly Disagree)	-	0.874
Legal Cynicism (”How much do you agree that…”)	A=0.488	A=0.058
Laws are made to be broken.	0.655	0.636
It’s okay to do anything you want so long as you don’t hurt anyone.	0.643	0.586
To make it there are no right and wrong ways anymore, only easy and hard ways.	0.695	0.754
Fighting between friends or within families is nobody else’s business	0.399	-
Nowadays a person has to live for today and let tomorrow take care of itself.	0.569	0.616
Perceived Violence (”During the past 6 months, how often was there…”)	A=0.828	A=0.647
A fight in this neighborhood in which a weapon was used?	0.894	0.878
A violent argument between neighbors?	0.755	0.769

Measure / Indicator	Loadings / Reliabilites (A) PHDCN (1995)	CCAHS (2003)
Gang fights?	0.918	0.901
A sexual assault or rape?	0.677	0.749
A robbery or mugging?	0.702	0.693
Violent Victimization	A=0.474	A=0.345
While you've lived in this neighborhood, has anyone ever used violence against you or any household member anywhere in your neighborhood?	1	1
Local Exchange ("How often do you and other people in the neighborhood…"	A=0.601	A=0.363
… do favors for each other?	0.832	0.803
When a neighbor is not at home… do you and other neighbors watch over their property?	0.773	0.748
… each other advice about personal things?	0.684	0.716
… have get-togethers where other people in neighborhood are invited?	0.613	0.620
… visit in each other's homes or on the street?	0.709	0.723
Kinship/Friendship Ties	A=0.768	A=0.564
How many of your relative or in-laws live in your neighborhood?	(0.31)	(0.24)
How many friends do you have in your neighborhood?	(0.31)	(0.24)
Attachment to Neighborhood	A=0.766	Unavail.
Do you like or dislike this neighborhood as a place to live?	(0.62)	-
If you had to move from this neighborhood, would you miss the neighborhood?	(0.62)	-

A.3 Crime Data

Two additional sources of crime measure were used: (1) the aggregated restricted access PHDCN-CS which includes the violent crime and homicide measures used by Sampson, Raudenbush, and Earls (1997), and (2) publicly-available geocoded Chicago Police Department (CPD) crime data for the three years after the CCAHS (Chicago Police Department 2020). The PHDCN-CS measures are provided as raw counts of incidents at the NC level. The geocoded CPD crime data permit constructing measure of crime incidents for smaller geographies such as the census blocks used in Chapter 2. Similar block-level crime data are not available for the years following the 1995 PHDCN-CS, preventing construction of a block-level two-wave panel. Full descriptives for crime data are provided in each chapter.

Appendix B

IDENTIFICATION PROBLEMS IN NEIGHBORHOOD STUDIES

This appendix provides an extended discussion of threats to causal identification in studies of neighborhood crime. It is based in part on the similar but shorter discussion in Lanfear, Matsueda, and Beach (2020), and draws heavily on

B.1 Potential Outcomes

This dissertation is concerned with the effect of social and physical characteristics of neighborhoods on crime. The potential outcomes causality framework applies the language of randomized controlled experiments to general questions of causal inference. This framework is useful for describing problems related to estimating causal effects in neighborhood crime and social control, the focus of this dissertation. For simplicity, this framework is typically illustrated, as here, with a binary treatment ($T = \{0, 1\}$), but it generalizes to multi-valued treatments. In this framework, τ_i, the causal effect of a treatment on unit i is defined as the difference between two potential outcomes: The outcome that would be observed if the unit receives the treatment ($Y_i(1)$) and the outcome that would be observed if the unit does not receive the treatment ($Y_i(0)$). Equation 1 depicts the unit treatment effect:

$$\tau_i = Y_i(1) - Y_i(0) \tag{B.1}$$

The fundamental problem of causal inference is that we only observe one of these potential outcomes for any given unit (Holland 1986). This renders estimation of the individual causal effect impossible—the individual causal effect is unidentified. If, however, treatment assignment is independent of these potential outcomes ($\{Y_i(0), Y_i(1)\} \perp\!\!\!\perp T_i$) we can estimate the average treatment effect (ATE) as the average difference in outcome between treated and untreated units:

$$
\begin{aligned}
ATE &= E(Y_i(1) - Y_i(0)) \\
&= E(Y_i(1)) - E(Y_i(0)) \\
&= E(Y_i|T_i = 1) - E(Y_i|T_i = 0)
\end{aligned}
\tag{B.2}
$$

To achieve identification in this manner, a series of assumptions must be made. The first key assumption is ignorability of treatment assignment, and the second is the stable unit treatment value assumption (SUTVA) (Rubin 1986), which has two components: consistency and absence of interference.

B.1.1 Ignorability

Ignorability is the assumption of independence between potential outcomes and treatment—that is, units of the treated group are not systematically affected more or less by treatment than would be the untreated. Equation (B.3) shows this assumption:

$$\{Y_i(0), Y_i(1)\} \perp\!\!\!\perp T_i \tag{B.3}$$

Ignorability does not rule out heterogeneity in treatment effects, but does require this heterogeneity be independent of treatment assignment. Ignorability may be satisfied with randomization as in a controlled experiment, but is unlikely to hold in observational research due to selection or confounding. In situations such as these, it may be possible to achieve ignorability by conditioning on all pre-treatment covariates X which predict both treatment and the outcome:

$$\{Y_i(0), Y_i(1)\} \perp\!\!\!\perp T_i|X_i,\ 0 < Pr(T_i = t|X_i) < 1 \tag{B.4}$$

The assumption shown in equation 4 is termed "strong ignorability" given covariates, which further requires positive probability of treatment at all levels of X. Controlling for all relevant pre-treatment covariates (X) is the primary difficulty for establishing causality in observational studies. Provided ignorability given covariates, we may estimate the conditional average treatment effect (CATE) as the expected value of equation 2—the average difference between treatment groups conditional on covariates.

B.1.2 Mediation and Sequential Ignorability

We may be interested in estimating the indirect effect of a treatment on an outcome via some mediator or mechanism, such as the effect of collective efficacy on crime via changes in the built environment .

$$\delta_i(t) = Y_i(t, M_i(1)) - Y_i(t, M_i(0)) \tag{B.5}$$

Equation (B.5) is the causal mediation effect, which is the difference in the outcome that would be observed due to the change in the value of the mediator occurring from treatment while holding treatment status (t) constant. Note the indirect effect includes additional potential outcomes—the mediator counterfactuals—that are never observed, and if there is no effect of treatment on the mediator $M_i(1) = M_i(0)$, there is no causal mediation effect. In causal mediation analysis, there are two additional causal effects of interest:

$$\zeta_i(t) = Y_i(1, M_i(t)) - Y_i(0, M_i(t)) \tag{B.6}$$

$$\tau_i = (Y_i(1, M_i(1)) - Y_i(0, M_i(0)) \tag{B.7}$$

Equation (B.6) is the causal direct effect (CDE), defined as all effects of the treatment on the outcome occurring through causal mechanisms other than the mediator. Equation (B.7) is the total effect, defined as the sum of the causal mediation effect and the causal direct effect, assuming no interaction between treatment and mediator. Note the total effect in mediation analysis is equivalent to the unit treatment effect (Equation (B.2)). Mediation analysis is a form of causal effect decomposition (VanderWeele 2014).

Consistent estimation of these causal effects requires extending the ignorability assumption into an assumption of sequential ignorability . This requires that the treatment assignment is ignorable, as before, conditional on included pretreatment covariates. It also requires that assignment of the mediator is ignorable conditional on both the treatment and included pretreatment confounders. Given X_i is a vector of observed pretreatment confounders, equations (B.8) and (B.9) define sequential ignorability (Imai, Keele, and Yamamoto 2010), provided non-zero probability of both treatment and mediator at all levels of their antecedent variables.

$$\{Y_i(t', m), M_i(t)\} \perp\!\!\!\perp T_i | X_i = x,\ 0 < Pr(T_i = t | X_i = x) < 1 \tag{B.8}$$

$$Y_i(t', m) \perp\!\!\!\perp M_i(t) | T_i = t, X_i = x,\ 0 < Pr(M_i = m | T_i = t, X_i = x) < 1 \tag{B.9}$$

Even under randomized treatment, equation (B.9)—mediator ignorability—is a strong and generally untestable assumption. In an observational setting, this is an especially strong assumption. Imai, Keele, and Yamamoto (2010) suggest using tests to estimate the sensitivity of causal mediation results to omitted confounders. Imai and Kim (2019) also show that the sequential ignorability assumption applies to causal inference in panel models using unit fixed-effects to adjust for omitted time-invariant confounders. In that setting, the treatment in each time period must be ignorable conditional on all prior treatment levels of the unit. Potential feedback between outcomes in one period and treatments and confounders in subsequent periods render identification challenging.

Models with multiple mediators also present a challenge to identification as conventional approaches are biased when mediators are correlated or interact with one-another. When these occur the individual pathways effects may not be identifiable at all even if sequential ignorability is otherwise satisfied (VanderWeele 2015). This dissertation features one analysis with multiple mediators: an estimation of the effect of past collective efficacy on present crime via multiple features of the built environment as well as present collective efficacy. Typical mediation approaches make the assumption of no interaction between mediators—these may be unrealistic if, for instance, criminogenic elements of the built environment display concentration effects or their effects interact with present collective efficacy.

In this dissertation, I use structural equations for my mediation analyses. These models make the assumption of no interaction between mediators and additionally assume linearity in exposure-mediator and mediator-outcome relationships. The causal mediation approach of (Imai, Keele, and Yamamoto 2010) is may be used as a robustness test as it relaxes the linearity assumption by permitting arbitrary functional forms but it is unsuitable in the present work as it does not permit estimation with multiple mediator paths. (VanderWeele 2015) suggests an inverse probability weighting approach to estimate average direct and indirect effects in the presence of multiple interacting mediators. This method performs poorly with continuous treatments—such as collective efficacy—making it inapplicable to the present analyses (VanderWeele 2015).

B.1.3 Consistency

Consistency is the assumption that the mechanism by which treatment is assigned can be ignored because the potential outcomes for units are independent of different treatment mechanisms. This assumption may also be stated as there being (1) no difference in potential outcomes within units across different version of any particular treatment level, or (2) only one unique form of each treatment level. This assumption is problematic for experiments where a researcher-assigned treatment may differ from the real-world treatment it is meant to mimic. It may also occur in observational research as a measurement problem where a given value of the treatment corresponds to different actual treatments or dosages. Note this is not equivalent to treatment effect heterogeneity. In treatment heterogeneity, the potential outcomes are fixed for individual units. Under a consistency violation, units are receiving different treatments with different unit-specific potential outcomes despite having the same measured treatment status. In observational designs, consistency is generally untestable but must be assumed to make causal inferences—a controversial problem in the statistics literature (VanderWeele 2015). One benefit to adherence to Holland and Rubin's oft-derided motto "no causation without manipulation" is that clarity with regard to the (at least theoretical) manipulation under consideration helps mitigate consistency violations (Hernán and VanderWeele 2011).

B.1.4 No Interference

The assumption of no interference requires that treatment assignment of one unit does not affect the outcomes of other units:

$$\{Y_i(0), Y_i(1)\} \perp\!\!\!\perp T_j, i \neq j \tag{B.10}$$

Two forms of interference are common when examining neighborhood processes: direct and via contagion (Ogburn and VanderWeele 2014). The difference between direct interference and interference via contagion is whether the effect of unit i's treatment on unit j's outcome is mediated by the outcome of unit i. Direct interference occurs when treatment of a unit directly affects the outcome of another unit: treatment of unit i essentially also treats unit j. For example , high collective efficacy in one neighborhood might produce guardianship for a nearby neighborhood which directly reduces violence there. Interference may also occur through contagion, in which the outcome of a treated unit—instead of the treatment itself—affects the outcome of another unit. For example, if high collective efficacy reduces violence in the focal neighborhood but that lowers retaliatory violence in a nearby neighborhood.

These two forms of interference may produce seemingly equivalent outcomes, but the differences between these forms of interference are consequential for theory and modeling. Interference may be addressed by modeling the interference process, such as with an exogenous spatial lag for direct interference or an endogenous lag for interference by contagion. Accounting for interference is important as it has been found empirically in studies of collective efficacy (Morenoff, Sampson, and Raudenbush 2001) and is explicitly assumed by the cascade mechanisms in broken windows.

B.2 Specific Issues

There are a number of prominent threats to identification in the analyses in this dissertation. I first focus on threats to ignorability, specifically key omitted variables, apparent reverse causality or reciprocality, and the related issue of how quickly causal processes operate. Then I discuss potential consistency violations and sources of interference.

B.2.1 Omitted Variables

Causal research on neighborhood crime has typically focused on relationships between informal social control (e.g. collective efficacy), crime, and disorder (Lanfear, Matsueda, and Beach 2020). Routine activity theory provides a useful language for considering omitted variables which may compromise identification of these relationships. Confounding is likely to occur if a model omits any variable that is related to the treatment and which influences the three necessary elements of predatory crimes—likely offenders, suitable targets, and capable guardians. In this dissertation, I suggest elements of the built environment which provide targets, attract offenders, and inhibit guardians are key omitted variables in neighborhood studies of crime. I hypothesize that these sources of opportunities are causally descended from collective efficacy because residents act collectively to eliminate what they recognize as criminogenic contexts. Because the built environment is slow to change, I expect this to be an effect with substantial lag time. The presence of criminogenic contexts may also influence neighborhood collective efficacy or moderate its effects on crime by presenting formidable or even intractable challenges. This effect should be immediate as evaluations of collective efficacy will take into account challenges that impact how effective collective action is likely to be.

Some studies have introduced additional social factors such as legal cynicism or police legitimacy (Kirk and Matsuda 2011; Sampson and Bartusch 1998) and (Anderson 1990) "code of the street" (Matsueda, Drakulich, and Kubrin 2006). On the one hand, their findings suggest it may be important to adjust for these to identify causal effects of informal social control. On the other, their designs typically cannot adjudicate between these variables being confounders or mediators of informal social control: causal directionality is established by assumption based on theory rather than tested empirically. If the direction of causality is different than assumed—such as when they operate as mediators—adjusting for these variables may introduce bias into estimates rather than reduce it. In this dissertation, I evaluate the role of police legitimacy and effectiveness in the neighborhood crime control system, combining the two into a police efficacy construct. While my theoretical framework suggests police efficacy precedes and moderates collective efficacy, I use repeated observations to evaluate the direction of effects.

In most analyses in this dissertation I must necessarily make the assumption that there are no other relevant omitted variables compromising identification. This is a strong assumption in complex systems like neighborhoods, but all effort has been made to include predictors implicated by neighborhood and place theories of crime—and to do so with careful attention to measurement and causal ordering. More problematic are potential omitted variables confounding the relationship between collective efficacy and the built environment—a relationship which has not been explored in past research. Processes operating at the metro level may generate confounding by differentially allocating investment and resultant development to neighborhoods (Dreier, Mollenkopf, and Swanstrom 2014; Logan and Molotch 2007).

Sensitivity tests for evaluating the threat of confounding are another approach to addressing omitted confounders. For example, Harding (2003), demonstrates a process in which he (1) simulates unobserved confounders with varying correlations with treatment and outcome, (2) determines how strong these relationships would need to be to invalidate his primary findings, and (3) evaluates the plausibility of the existence of these omitted confounders in light of observed covariates with comparable associations. Such sensitivity tests represent recognition that the focal causal effect may not be precisely identified due to omitted variables, but may be unlikely to be zero or of the opposite sign. In the last section of this chapter I use directed acyclic graphs to illustrate other scenarios for which sensitivity tests may be conducted to evaluate the threat to identification presented by omitted variables.

B.2.2 Reverse Causality

The presence of reciprocal pathways presents another potential threat to ignorability in neighborhood studies of crime. Broken windows, collective efficacy, and routine activity theories all feature some degree of reciprocality between their key causal factors. Broken windows states that informal social control is the primary mechanism restraining disorder, but pervasive disorder reduces social control capacity (Wilson and Kelling 1982). Collective efficacy is commonly described as a fully recursive model, though Sampson and Raudenbush (1999) and Sampson (2012) acknowledge crime feeds back directly on collective efficacy, possibly through fear or cynicism. In the original presentation of routine activity theory, Cohen and Felson (1979) describe a reciprocal relationship between predatory patterns of likely offenders and protective behaviors by potential targets, which evokes game theoretic approaches. In all cases, positive reciprocal effects will inflate estimates, while negative reciprocal effects will attenuate them. In either case, the causal relationship is not identified.

This concern may be addressed by considering micro-macro transitions and the necessary temporal ordering for these to occur. For example, broken windows specifies neighborhood-level mechanisms which are mediated by individual perception and action. Neighborhood disorder causes crime only by signaling low social control. Perceived low social control induces either offending or self-protective behavior in individuals. Self-protective behavior reduces actual social control, and thus induces offending as well. Changes in crime rates and quantity of neighborhood disorder are the aggregation of these individual behaviors. Temporal ordering and inter-level transitions resolve the apparent reciprocality problem.

Consider also collective efficacy's reciprocal relationship with crime. This process is temporally ordered and occurs through lower-level processes. Collective efficacy inhibits crime through interventions or offender decision-making, while crime inhibits collective efficacy through fear or cynicism. For both broken windows and collective efficacy, these effects can be estimated using repeated observations at the neighborhood level or observations of the intervening individual-level mechanisms. In the acyclic graph section of this subchapter I illustrate the use of repeated observations to address reverse causality.

A related but more problematic form of reverse causality is in the source of resident perceptions of collective efficacy. Results from multiple studies suggest that residents—at least in part—infer levels of collective efficacy based on observed crime and disorder (Hipp 2016; Matsueda and Drakulich 2016). Again, if the individual-level mechanism can be measured reverse causality can be addressed in the measurement stage as done by Matsueda and Drakulich (2016). If this cannot be done at the individual level, reverse causality can be modeled at the neighborhood level but it will remain ambiguous if observed feedback is due to individual updating of expectations for others' social control interventions or a suppressive effect of crime on actual intervention propensity.

B.2.3 Temporal Considerations

If relying on temporal order to resolve reverse causality, an important question is how quickly different causal pathways operate over time (see Taylor 2015). I propose collective efficacy controls crime immediately via informal control but also has a lagged effect by altering criminal opportunities in the built environment. Both of these processes occur simultaneously and continuously. Collective efficacy is conventionally described as a capacity for direct interventions against deviance (Sampson, Raudenbush, and Earls 1997). These interventions are immediate and aimed at stopping an ongoing or imminent activity. When interventions, or the perceived threat thereof, cease, so will their protective power.

In contrast, interventions via the built environment occur slowly but have enduring consequences. These interventions target recurrent unwanted activity or the threat of such. If successful, they can entirely remove the potential for these activities to occur. For example, collective action that shuts down a problem bar or clears a vacant lot might reduce crime on that block for years afterward. If collective efficacy declines in the future, it may reduce the likelihood of direct interventions but the problem bar or vacant lot does not immediately return. In this way, collective efficacy in the past may be as consequential as present levels for determining rates of crime. If this is accurate, I expect the present state of the built environment to mediate the effect of past collective efficacy on crime.

A related set of empirical questions—which I do not examine in this dissertation—are how long are the appropriate time lags for these effects and do they vary systematically across neighborhoods (see Taylor 2015 for an extended discussion). Consider the direct effect of collective efficacy. Collective efficacy is assumed to reduce crime in neighborhoods at least in part through a deterrence or normative mechanism: likely offenders refrain from attempting crime because they perceive the neighborhood has capable guardians. An important question is whether likely offender perceptions of collective efficacy closely mirror those of residents, or is there a substantial lag between those perceptions? If their perception of guardianship is rooted in the past—such as if offenders update perceptions slowly—it may induce an effect of past collective efficacy not blocked by present collective efficacy or the built environment.

We might consider this a reputational effect which would complicate estimation of causal effects of present collective efficacy.

As a final note on temporal considerations, it is important to state that over a sufficiently long period, every neighborhood social and physical characteristic is endogenous. This is because actors recognize the relationship between perceived problems and physical and social characteristics of neighborhoods—and they act to address both the problems and what they perceive as their underlying causes. And, when problems appear intractable, residents cease making interventions and those able to do so are likely to leave the neighborhood. A primary argument of this dissertation is that the capability to act efficaciously to address perceived problems is a key mechanism relating social structural (dis)advantage to crime, disorder, and neighborhood change.

B.2.4 Measurement and Consistency

The prior discussion raises the broader question: from where do perceptions of collective efficacy emerge?. Research focusing on residents suggests these perceptions are at least in part drawn from their observations of crime and disorder (e.g., Hipp 2016; Matsueda and Drakulich 2016). Residents who observe crime and disorder infer control capacity is weak, and those who observe their absence infer control capacity is strong. Less is known about offender perceptions, which are particularly consequential if collective efficacy inhibits crime via deterrence. Sampson, Morenoff, & Earls (1999:657), for example, suggest children know levels of child-centered control better than the adults from which surveys typically obtain measurements. Given evidence that most offending occurs near where offenders live (Bernasco and Block 2009) or are otherwise familiar (Carter and Hill 1979), likely offenders should have at least as accurate perceptions of social control capacity as residents. If likely offenders are better informed than residents, then conventionally measured collective efficacy is a contemporaneous—or even lagging indicator of social control capacity. This would close the reputational effect's backdoor causal path, permitting use of a lagged of collective efficacy as an instrument for present collective efficacy so long as any other mediating path is closed, such as the built environment.

This raises a secondary measurement problem. Consider if some unobserved built environment features are related to present collective efficacy and mediate past collective efficacy's effect on crime. For example, suppose past collective efficacy is causally related to current prevalence of street lights which inhibit crime. In this case, street lights will be an unobserved confounder preventing identification of the causal effects of present collective efficacy and the built environment on crime. This issue is further illustrated in the section on causal graphs at the end of this chapter.

In observational research, consistency is closely related to measurement. Because the researcher is not assigning a treatment to the exposed units, there is little worry that the treatment in question is an unrealistic approximation of "real world" treatment of interest. A greater concern is that a single level of the treatment may in fact represent different treatments. This dissertation proposes that conflicting evidence for causal effects of disorder on crime may in part be due to this form of consistency violation. Effects of disorder on crime are typically estimated based on variation in composite measures of multiple forms of disorder. In these composite measures, different configurations of disorder may result in the same measured value of the treatment. If each form of disorder produces a different criminogenic effect, it represents a consistency violation preventing identification of the treatment effect of interest. I address this problem by separating forms of physical disorder found in the built environment—such as abandoned buildings and vacant lots—into different measures, rather than combining them into indices as is common in this literature (e.g. Sampson and Raudenbush 1999).

B.2.5 Interference

Interference is a notable threat to causal inference in neighborhood research. The first potential source of interference is due to the mismatch between boundaries used as analytical units and "real" physical or social boundaries (Sampson, Morenoff, and Earls 1999; Taylor 2015). Spatial mismatches may result in units of analysis containing portions of both treated units and untreated units. This is a measurement problem in that it introduces bias into estimates by contaminating measures of some units with those from other units. While similar to other forms of interference in the manner it produces bias and in statistical methods which may be applied to address it, it differs in being induced by incorrect measurement rather than actual contagion or spillover effects. Unlike other forms of interference, in theory this might be addressed by using correct spatial units—though arguably a single correct spatial unit may not exist at all for neighborhoods, given the unavoidable presence of both social and spatial determinants in boundary-making practices.

Mobility of offenders is another plausible source of spatial dependence, but not necessarily interference. While offenders commit more crimes near home than far away, a substantial number of offenses still occur in locations distant from their residences (Bernasco and Block 2009; Carter and Hill 1979). If likely offenders radiate outward from their residences at random, it will result in dependence between crime in a focal unit and structural sources of motivation in nearby areas which decays with distance. This is commonly modeled with spatial error or, as done in this dissertation, spatial lag models. It is unlikely offenders only radiate outward at random, however. It is more likely they follow—like any other actors—efficient paths like major roads and public transit lines (e.g. Brantingham and Brantingham 1981). A developing area of research suggests digital trace data or novel survey methods may address this by permitting estimation of stocks and flows of people in and between neighborhoods (Browning, Pinchak, and Calder 2021).

This offender mobility will produce interference if it is in some way induced by the treatment in question—collective efficacy, the built environment—either directly or via crime rates. For example, a body of work suggests violence, particularly gang-related violence, is often retaliatory in nature (Block 1977). The presence of rival gangs in different neighborhoods may induce interference by contagion in measures of violent crime. This will occur if collective efficacy reduces violence in one neighborhood which results in an elimination of subsequent retaliatory violence in another neighborhood. Note that this form of interference is closely related to offender mobility, as retaliatory violence may involve offenders traveling to other neighborhoods either for the initial attack or the retaliation. Consequently, it is possible—even likely—that both forms of interference occur at the same time.

It is also likely that, if engaged in a search process for opportunities, likely offenders will seek out areas likely to be target rich and guardian poor. Drawing from rational choice criminology (Cornish and Clarke 1986), what qualifies as target rich or guardian poor depends on the crime: for robbery, this may be poorly lit areas with cash-focused businesses, but for burglary it may be residential neighborhoods with single-family homes unoccupied during work hours. If likely offenders travel to reach areas of high opportunity, it is likely they will be engaged in at least a passive search process during their travel. This may result in direct interference which increases crime along travel routes to the high opportunity location. A particularly high opportunity place may also exert negative interference if the opportunities presented are sufficient to cause offenders in nearby areas to ignore inferior local opportunities. In this way features of the built environment may generate interference in part via the target selection or search process of likely offenders (Browning, Pinchak, and Calder 2021).

Lastly, research on spatial neighborhood effects suggests collective efficacy exerts beneficial effects in adjacent neighborhoods (Sampson 2012; Sampson, Morenoff, and Earls 1999). The mechanism for this spatial effect has not—to my knowledge—been elaborated. If it exists, it may operate through the processes already described, such as reducing initial and thus retaliatory violence or impeding offender mobility (e.g. Greenberg, Rohe, and Williams 1982). Another possibility lies in mobility of residents: As with likely offender mobility, if residents travel beyond their neighborhood but engage in interventions at least partly based on the collective efficacy of their home neighborhood, it could induce direct interference. Testing this hypothesis would require collecting new data on intervention behaviors of residents outside their neighborhoods, but adjusting for it statistically could potentially be accomplished with a spatial lag of collective efficacy—though the mechanism would remain ambiguous.

B.3 Directed Acyclic Graphs and Ignorability

Directed acyclic graphs (DAGs) provide a useful for tool for demonstrating potential violations of ignorability. The following diagrams depict observed variables in black text and estimable relationships between them in solid black arrows. Unobserved variables are in outlined text and relationships involving unobserved variables are in dashed lines

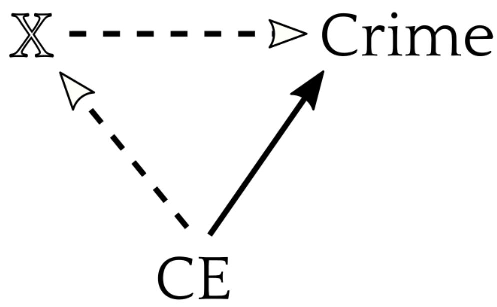


Figure B.1: An omitted mediator.

to indicate they cannot be estimated. Pathways which are identified in a DAG are typically non-parametrically identified—that is, they are agnostic to functional forms and the presence of interactions. This discussion focuses on relationships within and between neighborhoods—in line with the main theories under examination in this work—but similar issues apply for different units and at different scales. Even restricted to the level of neighborhoods, this discussion is not exhaustive: neighborhoods are complex systems featuring many processes occurring simultaneously. They cannot all be considered at once, but I believe I consider those most relevant to the question of how the built environment mediates the effect of collective efficacy on crime. While DAGs may be applied to interference problems (e.g. Ogburn and VanderWeele 2014), I do not illustrate interference in this section as it provides little additional clarity over the prior section.

Figure B.1 depicts a simple model where collective efficacy predicts crime directly and through one or more unobserved mediators (X). For simplicity, assume adjustment for relevant variables which precede collective efficacy and influence crime. In Figure B.1, the omitted variable is only a mediator between collective efficacy and crime. Omitting it has no consequence for estimating the total effect of collective efficacy on crime, but including the omitted variable would increase explained variance and tell us more about how collective efficacy influences crime—the omitted variable can be considered a causal mechanism. For the full mediated causal path to be identified, assignment of the treatment (CE) and the mediator (X) must satisfy sequential ignorability. There

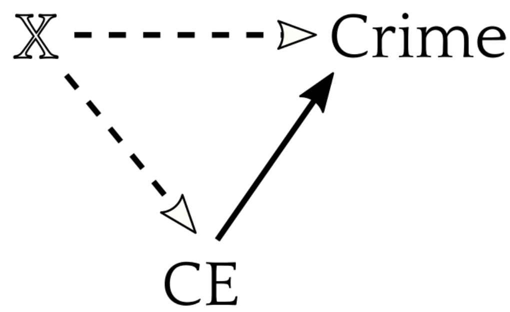


Figure B.2: Spuriousness.

are many candidates for omitted (but inconsequential) mediators, but the present work focuses on criminal opportunities, particularly criminogenic features of the built environment.

Figure B.2 includes the same variables but inverts the direction of causality between collective efficacy and the omitted measure. X is now a preceding omitted variable which renders the relationship between collective efficacy and crime partly spurious. This variable must be adjusted for to identify the causal effect of interest. The present work suggests criminogenic features of the built environment as a candidate for these immediate effects on crime and collective efficacy. Because the built environment changes slowly, it is not a plausible mediator for present collective efficacy, though it may moderate its effects. Social factors like legal cynicism or satisfaction with police (Kirk and Matsuda 2011; Sampson and Bartusch 1998) may also occupy this role, though they could just as plausibly be mediators for collective efficacy or simply share the same antecedents. Adjudicating between different causal directions requires repeated observations or instrumental variables.

If ignorability cannot be achieved by directly conditioning on all relevant variables—that is some source of spuriousness is unobserved—identification can be achieved using an instrumental variable. Figure B.3 uses past collective efficacy as an example under the assumption that the only pathway by which past collective efficacy impacts crime is via present collective efficacy or included controls (again, hidden for simplicity). This is a strong and generally untestable assumption. Instrumental variables also assume a monotonic

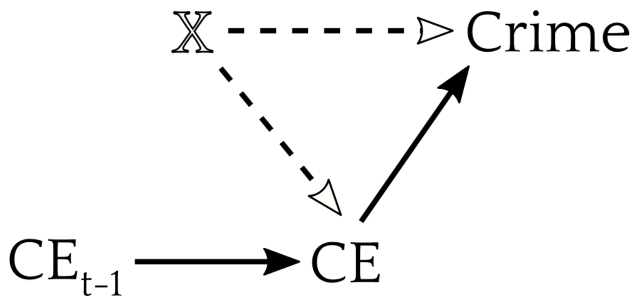


Figure B.3: A valid instrument.

relationship between instrument and treatment. The estimated causal effect provided an instrument is restricted to the subsample for which the instrument induced a change in the treatment—the local average treatment effect (LATE), sometimes called the complier average causal effect.

As an example of instrumental variables, Sampson and Raudenbush (1999) used a series of models with (1) reciprocated exchange and resident attachment to the neighborhood as instruments for collective efficacy, (2) mixed land use as an instrument for disorder, and (3) prior homicide as an instrument for present homicide and robbery. Using these instruments makes the strong assumptions that (1) reciprocated exchange and attachment do not influence crime or disorder through any pathways other than via collective efficacy, (2) mixed land use does not influence crime or collective efficacy except via disorder, and (3) prior homicide does not influence disorder or crime except via present homicide. The present work and recent research by others suggest mixed land use directly influences crime (Wo 2019) and prior crime depresses collective efficacy (Sampson 2012). Due to the interdependence of neighborhood processes, instrumental variables are not a promising route to causal identification unless they are produced via interventions.

Figure B.4 depicts a violation of the exclusion assumption in which past collective efficacy causes one or more of the relevant omitted variables. In this case, use of the instrument will not identify the effect of present collective efficacy on crime because of the backdoor path via X. The present work suggests some characteristics of the built

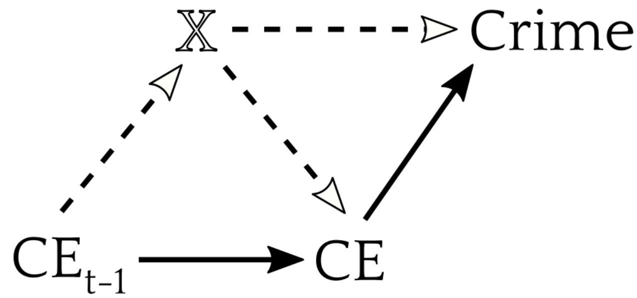


Figure B.4: Exclusion restriction violation.

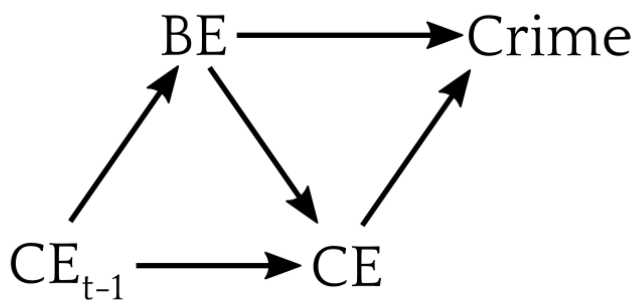


Figure B.5: Mediation model.

environment occupy the role of X here by presenting opportunities which facilitate crime while impacting present collective efficacy—but these opportunities may be removed due to collective action of residents, making them dependent on past collective efficacy. While the direct effect of collective efficacy on crime is not identified here, the total effect of past collective efficacy is because the omitted path is entirely descended from past collective efficacy.

If we observe and include the previously omitted mediator, we arrive at Figure B.5. In this model, the effect of present collective efficacy on crime is identified as is the mediation of past collective efficacy through the built environment. Note here the built environment serves as a post-treatment confounder for present collective efficacy which violates sequential ignorability (Imai et al. 2011). Adjusting for the built environment is required to identify the path from present collective efficacy to crime but doing so introduces bias into the estimated intertemporal collective efficacy path. The mediated effect of past collective efficacy on crime via present collective efficacy is thus unidentified.

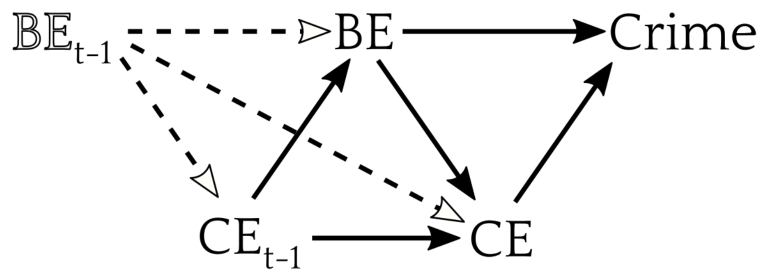


Figure B.6: A seemingly valid specification.

Even in a system with no unobserved variables, some causal effects may not be estimable without making additional assumptions, such as treatment homogeneity (Imai et al. 2011).

Including the relevant omitted variables—here the built environment—can close the problematic pathways and render our effect of interest identifiable. Figure B.6 depicts a DAG in which the built environment is observed. Because the present built environment impacts present collective efficacy, it is logical to include the past built environment in this diagram, though it may be unobservable. Here the past built environment influences both past and present collective efficacy. In this example, the effects of the present built environment and collective efficacy on crime are identified even though none of the other pathways are. In this situation, the total effect of past collective efficacy on present crime cannot be estimated; the first stage of our sequential ignorability has been violated. The mediation pathway from the built environment to crime via collective efficacy would be identified here if all impact of the past built environment on present collective efficacy was mediated by past collective efficacy and the present built environment.

We might then consider the consequences of additional omitted variables with varying relationships with the observed variables and unobserved past built environment. In Figure B.7, I include an unobserved variable X which is descended from the past built environment and collective efficacy and influences present collective efficacy. Candidates for X include elements of the built environment for which we do not have measures but increase (or decrease) collective efficacy, such as public spaces which increase inter-

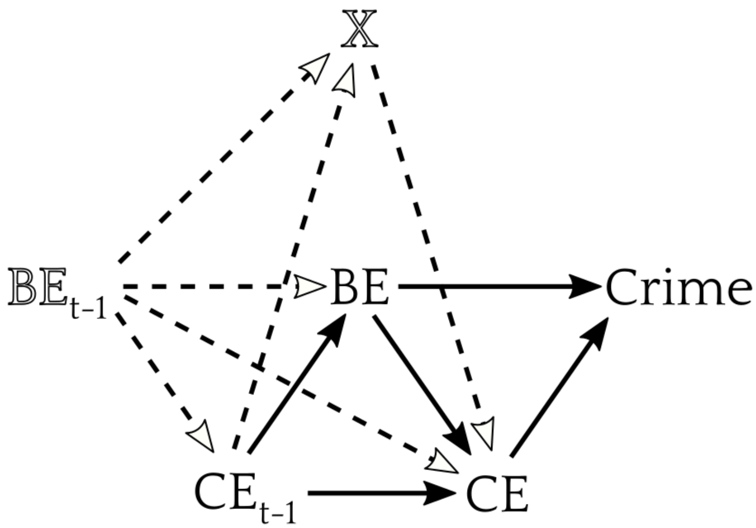


Figure B.7: A non-problematic omitted variable.

action between residents and foster collective efficacy. Another obvious candidate for X here is crime in the past period, which depends on both collective efficacy and the built environment and is known to impact future collective efficacy (Sampson 2012). Investment in the neighborhood from outside sources may also occupy a similar role but operating through the present built environment. So long as these omitted variables operate only through observable antecedents of present crime—collective efficacy or the built environment—they do not compromise our ability to identify the direct causal effects on crime. The causal mediation paths from past collective efficacy through either built the environment or present collective efficacy are not identified here however.

An omitted variable X which causes crime, as seen in Figure B.8, becomes more problematic. If it also causes present collective efficacy or the built environment, or—as shown—is caused by any unobserved antecedent of the built environment or present (but not past) collective efficacy, it will induce bias in our causal estimates of interest. This is likely to be the case for unobserved features of the built environment which provide criminal opportunities. This will also occur if past crime exerts a direct effect on present crime that is not mediated by collective efficacy or the built environment. Fortunately, it is possible

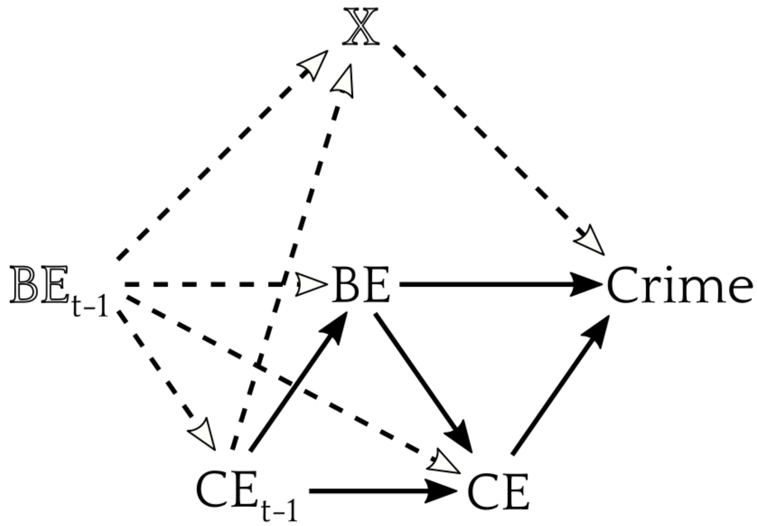


Figure B.8: A problematic omitted variable.

to test model sensitivity to unobserved confounders of this sort using methods proposed by Imai, Keele, and Yamamoto (2010). This sensitivity test procedure is similar in principle to that of Harding (2003) in that it simulates varying levels of confounding to determine how strong an omitted confounder would need to be to alter substantive findings.

Appendix C

BUILT ENVIRONMENT MODERATION

Early intervention in the built environment may have the added benefit of reducing future social control burdens. The absence of criminogenic features may explain low crime in areas lacking collective efficacy. Conversely, the presence of criminogenic features may make crime "sticky" even in the presence of concerted action by residents (St. Jean 2007). This means collective efficacy could be more effective at restraining crime in the absence of environmental features that inhibit the exercise of informal control. Consequently, I expect characteristics of the built environment to moderate the effect of collective efficacy on crime.

This alternate set of models tests whether features of the built environment moderate the association between collective efficacy and crime. These models mirror the prior models of crime but introduce interaction terms between collective efficacy and the built environment features. Based on my theoretical framework, I expect all interactions between collective efficacy and built environment characteristics to be positive because criminogenic features of the environment will attenuate the negative the effect of informal social control on crime.

C.1 Crime and Moderation of Collective Efficacy Results

The last set of models augments the original set examining associations with crime with interaction terms between collective efficacy and each of the hypothesized criminogenic built environment features. Interaction terms permit evaluating whether these features present challenges—"ecological disadvantage" in St. Jean (2007) terms—which are resistant to social control efforts; that is, locations where the returns to collective efficacy are low. Given the weak associations between collective efficacy and each form of crime, and the modest sample size which results in underpowered tests of interaction, these results should be interpreted with caution. Only very strong relationships are likely to be detected, but they may also be the result of sampling error and excessive partitioning of limited variation.

Table C.1: Negative binomial estimates of crime.

Level	Homicide	Gun Assault	Robbery	Violent	Property
Neighborhood					
Coll. Eff	-0.09	-0.03	-0.07	**-0.09**	**-0.06**
(2001)	(0.11)	(0.05)	(0.04)	**(0.04)**	**(0.03)**
Disadv.	**0.54**	**0.69**	**0.22**	**0.38**	**-0.09**
	(0.11)	**(0.05)**	**(0.04)**	**(0.04)**	**(0.03)**
Stability	-0.03	-0.02	**0.16**	**0.14**	**0.29**
	(0.13)	(0.06)	**(0.05)**	**(0.04)**	**(0.03)**
Hispanic /	**-0.35**	**-0.16**	**-0.41**	**-0.33**	**-0.23**
Immigrant	**(0.11)**	**(0.05)**	**(0.04)**	**(0.03)**	**(0.03)**
Density	**0.24**	0.06	**0.25**	**0.16**	**0.09**
(Neighb.)	**(0.11)**	(0.06)	**(0.05)**	**(0.04)**	**(0.03)**
Block					
Abandoned	0.17	**0.21**	**0.10**	**0.14**	**0.07**
	(0.09)	**(0.04)**	**(0.03)**	**(0.03)**	**(0.02)**
Bars	0.14	0.02	-0.05	-0.01	-0.01
	(0.11)	(0.05)	(0.03)	(0.03)	(0.02)
Commercial	-0.20	0.03	**0.26**	**0.20**	**0.11**
Dest.	(0.16)	(0.07)	**(0.05)**	**(0.04)**	**(0.04)**
Liquor	-0.04	0.04	0.03	0.03	0.00
	(0.10)	(0.04)	(0.03)	(0.03)	(0.02)
Mixed Use	0.24	0.11	**0.15**	**0.09**	**0.09**
	(0.14)	(0.06)	**(0.04)**	**(0.04)**	**(0.03)**
Parking	0.12	0.06	**0.07**	**0.08**	**0.09**
	(0.09)	(0.04)	**(0.03)**	**(0.03)**	**(0.02)**
Recreation	0.00	0.04	**0.09**	**0.08**	0.03
	(0.10)	(0.04)	**(0.03)**	**(0.03)**	(0.02)
Vacant	0.07	0.04	-0.01	0.00	-0.01
	(0.08)	(0.04)	(0.03)	(0.03)	(0.02)
Density	0.08	0.11	**0.10**	**0.18**	**0.09**
(Block)	(0.15)	(0.07)	**(0.04)**	**(0.03)**	**(0.03)**
Density	**-0.59**	**-0.36**	**-0.09**	**-0.13**	**-0.05**
(Block)^2	**(0.21)**	**(0.08)**	**(0.03)**	**(0.03)**	**(0.02)**
CE x	-0.07	**0.11**	0.03	**0.06**	0.04
Abandoned	(0.08)	**(0.04)**	(0.03)	**(0.03)**	(0.02)
CE x Bars	-0.02	-0.04	-0.04	-0.03	-0.02
	(0.12)	(0.05)	(0.04)	(0.03)	(0.03)

Level	Homicide	Gun Assault	Robbery	Violent	Property
CE x Commercial Dest.	-0.11 (0.15)	0.02 (0.06)	0.08 (0.05)	0.05 (0.04)	0.03 (0.04)
CE x Liquor	-0.07 (0.10)	0.01 (0.04)	-0.04 (0.03)	-0.02 (0.03)	-0.02 (0.02)
CE x Mixed Use	0.22 (0.13)	-0.00 (0.06)	0.01 (0.04)	0.00 (0.04)	0.02 (0.03)
CE x Parking	0.03 (0.09)	-0.04 (0.05)	0.05 (0.03)	0.01 (0.03)	**0.06** **(0.03)**
CE x Recreation	-0.00 (0.10)	0.04 (0.05)	0.04 (0.03)	0.02 (0.03)	-0.01 (0.03)
CE x Vacant	0.05 (0.09)	-0.03 (0.04)	-0.03 (0.03)	-0.03 (0.03)	-0.03 (0.02)

Table C.1 contains point estimates from the negative binomial models of crime with interactions between collective efficacy and the built environment features. As this table reveals, a number of interaction terms are of large magnitude, particularly for homicide, but most are imprecisely estimated. The only interactions significant at a conventional 95% level are for abandoned buildings predicting gun assaults and any violence, and parking predicting property crime. These three interactions are all positive as expected, but under multiple testing, one would expect to obtain a similar number of significant interactions due to chance; this is not a particularly noteworthy finding. Interactions are notorious for making strong demands of the data, in terms of statistical power, so it is unsurprising that little is found here. Similar results–though opposite in sign–are found interacting built environment features with disadvantage.

Nonetheless, these results may be indicative of violent crime in higher collective efficacy neighborhoods being concentrated in a small number of locations with abandoned buildings. As an examination of this, a cross-tabulation of gun assaults (not shown) reveals that over 58% of gun assaults in neighborhoods in the top quartile of collective efficacy occur on blocks in the top quartile of abandoned buildings. In neighborhoods in the bottom quartile of collective efficacy, this value is only 28%. That is, in low collective efficacy neighborhoods, gun assaults are fairly evenly distributed across blocks regardless of the concentration of abandoned buildings. In high collective efficacy neighborhoods, gun assaults are found where abandoned buildings are concentrated. This relationship might reflect what St. Jean (2007:220) describes as efforts by efficacious residents to limit serious crime to particular areas of their neighborhoods due to the inability to eliminate it entirely.

Appendix D

POLICE EFFICACY AND LEGAL CYNICISM

Note that I place procedural justice—fairness in police actions—as a component of police efficacy. Procedural justice independently reduces offending through effects on legitimacy (Tyler 2006). I see this as analogous to how collective efficacy may impede offending via internalization of norms of behavior (Sampson 2012). Sampson and Bartusch (1998) and Kirk and Matsuda (2011) capture this normative component using the concept of legal cynicism. It is noteworthy that Kirk and Matsuda—but not Sampson and Bartusch—combined police effectiveness with normative orientation toward the law in their definition of legal cynicism. Kirk and Matsuda found this form of legal cynicism predicted weaker collective efficacy which in turn predicted increased individual probabilities of arrest. They theorized that legal cynicism cuts off police as a perceived available route to solve problems.

In my framework, I distinguish between police efficacy—the collective belief in the ability to call on law enforcement—from legal cynicism—the collective belief in the irrelevance of legal norms. I assume the availability of formal social control for problem solving is captured by police efficacy rather than legal cynicism. Theory on collective efficacy (Sampson 2012) and police legitimacy (Tyler 2006) suggests legal cynicism is at least in part a result of collective efficacy and police legitimacy—a component of police efficacy—rather than an antecedent. Legal cynicism arises from the ineffectiveness of institutions of social control. Disentangling legal cynicism and police efficacy and testing their causal order requires measurement models and longitudinal data or instrumental variables. While not a primary focus of this chapter, I examined whether legal cynicism and police efficacy are separable constructs, and how legal cynicism is related to other neighborhood structures.

In support of Sampson and Bartusch (1998), I found the indicators of legal cynicism and police efficacy loaded on distinct factors in both waves of data. These legal cynicism and police efficacy factors are, further, nearly uncorrelated in 1995 ($\rho = -0.04$, $t = -1.72$) and only weakly correlated in 2003 ($\rho = -0.13$, $t = 2.49$). Consequently, I separate police efficacy from the indicators of legal cynicism. Results from neighborhood-level models also indicate legal cynicism is essentially unrelated to other social structural characteristics. Further, legal cynicism is much less reliably estimated at the neighborhood level than most other constructs, despite being reliable at the individual level. It appears to be determined mainly by individual socioeconomic status. This suggests legal cynicism may not be a meaningful neighborhood-level social structure the way collective efficacy and police efficacy appear to be. I returned to multi-level measurement models to explore individual-level legal cynicism as a result of neighborhood-level structures and conditions.

In 1995, once adjusting for individual-level controls, legal cynicism is primarily related to neighborhood disadvantage and secondarily to collective efficacy. It appears unrelated to police efficacy or even the present homicide rate. In 2003, none of the neighborhood measures significantly predict legal cynicism. In both years, legal cynicism is far more strongly predicted by individual socioeconomic status than any other measures. As a result of these findings, I omit legal cynicism from my neighborhood-level analyses.

COLOPHON

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