Path Dependence in Geographic Crime Patterns

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Path Dependence in Geographic Crime Patterns

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A Dissertation Submitted to The Graduate School at the University of Missouri-St. Louis
in partial fulfillment of the requirements for the degree
Doctor of Philosophy in Criminology and Criminal Justice

August
2020

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Acknowledgement

This work was supported, in part, by the Charles G. Huber, Jr. Endowed Dissertation Fellowship in Criminology and Criminal Justice.
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Abstract

This dissertation argues that status quo bias in crime location choice has substantial effects on geographic crime patterns. Offenders often re-select prior crime locations when they commit crimes. Mainstream theories argue this is because such locations are objectively more suitable for crime and thereby attract offending behavior at higher rates. I contend that locational suitability is only one consideration and that offenders may re-select a location that has been established as a status quo option, despite availability of more optimal alternatives. When individuals re-select prior crime locations, crimes will increasingly concentrate and create hotspots that are stable over time and resistant to location change. These propositions are tested in two parts. First, I analyze a sample of 9,527 crimes occurring in St. Louis, Missouri (2017-18) to show how prior crime locations have higher odds of being selected than alternatives, net of observed and unobserved locational suitability factors. Second, I build an agent-based model to simulate the crime location choice process. Two experiments are conducted on the model to compare macroscopic patterns under different decision making assumptions. The first experiment shows that aggregate crime patterns are more concentrated and stable over time when offenders have a status quo bias. The second experiment shows that crime hotspots are resistant to locational change when offenders have a status quo bias, and that person-based and network-based interventions are necessary to override the history effects. The combined results suggest that status quo bias is present in offender decision making, and it is sufficient to generate concentrated, chronic crime problems. Crime policy should be cautious of the potential limits of place-based crime reduction strategies and consider person-based and network-based approaches as possible alternatives.
Chapter 1. Introduction

This dissertation introduces a new idea about how individuals make decisions when committing crimes. The primary aim is to examine how this process can explain geographic patterns of crime. The argument states that individuals often commit crimes in the same locations where they and their co-offenders have offended before. This bias towards re-selecting the same places is because of a choice preference towards the status quo option, not because the location is objectively more suitable than other locations, as proposed in mainstream theories. This mechanism is one example of a general process known in other fields as *path dependence*, which refers to positive feedback and self-reinforcing change in a phenomenon over time (Arthur, 1994; David, 1994; Mahoney, 2000; Pierson, 2004).

The macroscopic consequences of path dependence are profound. When previous crime sites are continually re-selected by offenders, crime events concentrate in space and create chronically risky hotspots. This is consistent with empirical evidence that crime is geographically concentrated (Brantingham et al., 1976; Lee et al., 2017; Sherman et al., 1989; Weisburd, 2015) and that crime patterns are generally stable over time (Andresen et al., 2017; Andresen & Malleson, 2011; Braga et al., 2010; Sampson, 2012; Spelman, 1995; Taylor, 1999; Weisburd et al., 2004). If path dependence characterizes a substantial portion of crime-related processes, it will shake many areas of criminological inquiry. This dissertation argues that it does and explains how crime theory and policy are affected as a result.

The path dependence perspective is based on decades of work in social science. Research in behavioral economics, for example, finds that individual behavior is
influenced by *status quo biases* that preference an established reference point and overrule rational considerations (Kahneman et al., 1991; Samuelson & Zeckhauser, 1988). Humans are more likely to repeat old habits than forge new paths. This can explain why economic industries cluster together (Arthur, 1986; Krugman, 1991), organizations are resistant to change (David, 1994), and most everyone’s computer uses the same “QWERTY” keyboard configuration (David, 1985). Path dependence can also explain why seemingly ‘small’ or chance events can have substantial impacts on future outcomes and therefore cannot be treated as ‘noise’ (Arthur, 1994; Pierson, 2004). A particular pattern can become ‘locked-in’ through positive feedback dynamics, making it extremely difficult to change course (Arthur, 1988a, 1990a; Arthur et al., 1987). Both the mechanisms that generate ‘lock-in’ and those that permit ‘exit from lock-in’ are therefore of great interest theoretically and for developing effective policy.

One provocative feature of path dependence theory is that the hypothesized mechanisms tend to contradict conventional theories. In economics, for instance, neoclassical theory is built on the assumption of *decreasing* returns and optimal equilibriums, whereas path dependence implies *increasing* returns and nonlinear dynamics (Arthur, 1990a). In the criminological context, mainstream theories are built on the assumption that crime occurs in suitable locations for this type of behavior. As discussed in Chapter 2, individuals are expected to offend in places with low social controls (Bursik Jr & Grasmick, 1999; Sampson et al., 1997; Shaw & McKay, 1942), plenty of suitable targets (Clarke & Felson, 1993; Cohen & Felson, 1979), and the presence of ‘risky’ facilities (Brantingham & Brantingham, 1995; Eck et al., 2007) because these characteristics are perceived by the offender to be suitable for crime
Crimes should be spatially concentrated to the degree that suitability factors are also concentrated. Because of this correlation between crime and place conditions, this perspective asserts that “place matters” (Sampson, 2013; Stark, 1987; Weisburd & Eck, 2018b; Weisburd et al., 2016).

By contrast, path dependence theory suggests that the pull towards suitable places can be overruled by a status quo bias towards re-selecting previous crime sites, regardless of how suitable other locations may be. In other words, offenders prefer to return to their old crime sites. It follows that crime hotspots may not be the ‘best’ places for crime. Instead, hotspots may be those locations that were established as status quo options early-on and attracted more offending behavior. The mechanism is hypothesized to operate within individuals and across individuals within the same co-offending network. This causes crime patterns to become concentrated and stable over time. This perspective claims that “history matters” and it can override the influence of place.

Mainstream theory and path dependence have diverging implications for crime policy. The former suggests that crime reduction strategies should target the place characteristics of high crime areas that make them suitable. Decreasing location suitability will cause offenders to avoid selecting that area again and generate crime reductions. This is done by increasing guardianship (Reynald, 2016), collective efficacy (Sampson et al., 1997), eyes on the street (Jacobs, 1961), and place management (Eck, 1994; Eck & Madensen, 2018). It could also involve increasing formal controls through hot spots policing (Braga et al., 2014; Braga & Weisburd, 2010) or changing the physical structure of the environment, such as the removal of urban blight (Branas et al., 2018).
and disorder (Wilson & Kelling, 1982), increasing defensible space (Newman, 1972), or through other forms of crime prevention through environmental design (Jeffery, 1977) or situational crime prevention (Clarke, 1995). The crime reduction effects of these interventions occur by making the area less attractive or conducive to criminal activity (Keizer et al., 2008; St. Jean, 2008). If place matters, then high crime places need to change to reduce crime there.

On the other hand, path dependence suggests that changing place conditions may be insufficient. Instead, emphasis should be placed on the habitual nature of decision making by focusing on those individuals that are most likely to re-select the same high crime sites. It also means that stopping the social transmission of historical influences within a crime network is of paramount importance. The aim of these interventions would be breaking links with history, either within individuals or within social networks. In reality, some combination of place and history influence crime patterns, but the relative contribution of these processes in any given context will determine the effectiveness and efficiency of different types of crime policies.

This dissertation begins the scholarly discussion of path dependence as an important criminological process. Although path dependence can be applied to a wide range of criminological topics, the focus here is on geographic crime patterns. The next two chapters further outline the “place matters” perspective of mainstream theories (Chapter 2) and the “history matters” perspective of path dependence (Chapter 3). A micro-macro framework is used as a conceptual model to illustrate how these perspectives differ. My theoretical approach is that of generative social science, which examines how microscopic interactions explain macroscopic regularities “from the
bottom up” (Epstein, 1999, p. 42). This is advantageous because I can incorporate theory across levels of explanation. It also provides a viable means for investigating the nonlinear dynamics of path dependence by way of simulation, which will become clearer in the coming chapters.

The first stage of analysis uses a sample of N=9,527 UCR Part I crimes from St. Louis, Missouri (2017-2018) to show that offenders return to prior crime sites where they and their co-offenders have previously selected for crime (Chapter 4). The empirical findings demonstrate the hypothesized status quo bias that serves as a microscopic mechanism of path dependence. In the second stage of analysis, agent-based modeling is used to experimentally manipulate the offender choice calculus to show how status quo bias combines with other processes to generate aggregate patterns of crime that are more concentrated, more stable, and more resistant to changes in location suitability than when history effects are absent (Chapter 5). The simulation results show that the success of place-based interventions is contingent on the presence of path dependent history effects; when history effects are strong, even large place-based changes do not always generate crime reductions as intended. Alternatively, person-based and network-based interventions show promise for generating crime reductions at target locations. The final chapter (Chapter 6) discusses implications of the research, suggesting that path dependence theory be incorporated more explicitly into criminological inquiry.
Chapter 2. On Current Theories in Criminology

Theories in criminology are predominately focused on explaining the uneven distribution of crime and the processes that reproduce this pattern over time. As introduced in Chapter 1, the mainstream approach is grounded in the assumption that crime occurs at times and places that are most suitable for this behavior. By *suitable* I mean that crimes are appropriate, acceptable, or advantageous in a given context and therefore fit the conditions in which they occur. If conditions are not suitable, mainstream theories expect crime not to occur there. Given this assumption, the role of the criminologist is to identify the optimal conditions that increase the likelihood of crime. Through the lens of the routine activity approach, the appropriate context for crime includes the confluence of motivated offenders, suitable targets, and no capable guardians (Cohen & Felson, 1979). From the standpoint of social disorganization, a lack of social control creates the suitable conditions allowing crime to thrive (Sampson et al., 1997; Shaw & McKay, 1942). Other theories propose other suitability conditions. The sources of suitable conditions vary greatly across theories, but the assumption is the same: crime occurs where conditions are suitable, and changes to the suitability of an area is expected to change the amount of crime that occurs there. Pragmatically speaking, changing place conditions (e.g., increasing social controls, decreasing unprotected target availability) will change the pattern of crime, and thus a range of place-based approaches for reducing crime problems can be prescribed.

This chapter argues that mainstream theory in criminology is built on the assumption that crime clusters in places that are suitable for it to occur. If social and environmental conditions of a place change, crime is expected to change as well. This
perspective has coined the phrase “place matters” (Sampson, 2013; Weisburd et al., 2016).

One important feature of theories in the suitability perspective is that the social system is presented as a unique, predictable equilibrium. This means that stabilizing forces will continuously shape crime patterns to converge with the distribution of optimal crime conditions. Modeling these equilibrium conditions can be done with error correction models, which seek to estimate how quickly the dependent variable $Y$ returns to equilibrium after a change in independent variable $X$ (De Boef & Keele, 2008) (for a criminological example, see Rosenfeld & Levin, 2016). Offenders learn which social and environmental conditions are associated with good targets and adjust their target selection patterns accordingly (Brantingham & Brantingham, 1981), paralleling a Bayesian updating process (Anwar & Loughran, 2011). Stated differently, crimes tend to “select” into environments where they are well fit, much like in biological systems when a dominant species selects into specific environments where it is well fit for survival. Historical “accidents” will correct themselves, because crimes committed in unfit conditions tend not to be repeated.

To give a criminological example of this crime selection process, suppose that a group of young offenders chooses to break into parked vehicles in neighborhood $A$, but they find items of only limited value and no cash (low target suitability). The group is nearly caught in the act by a patrolling police car and later scolded by a passing resident for tampering with vehicles (high social control). Now suppose that later the same group of offenders breaks into vehicles in adjacent neighborhood $B$, finding cash and valuable goods without being confronted by passersby. Through an updating process, the
offenders learn not to search for targets in neighborhood A again because rewards are not high enough to overcome perceived risks, and they likely return to neighborhood B during future target searches rather than neighborhood A (Brantingham & Brantingham, 1993; Clarke, 1995; Clarke & Cornish, 1985). Now suppose further that other potential offenders experience similar circumstances. They too will learn that neighborhood B is suitable for crime and also commit crimes there. This is one way in which locational suitability processes drive the uneven distribution of crime, through traditional mechanisms of offender decision making.

**Mainstream Functional Explanations**

The above example is one application of what Stinchcombe (1987) describes as “functional causal imagery.” Functional causal structures are those “in which the consequences of some behavior or social arrangement are essential elements of the causes of that behavior” (Stinchcombe, 1987, p. 80). This type of explanation involves (1) a consequence C which is a homeostatic variable that tends to be maintained and acts as a cause of the behavior, (2) the behavior B which has a causal impact on the consequence C, and (3) other causal forces or tensions T which tend to disrupt the stability of C. Figure 2.1.1 illustrates the elementary causal structure of functional explanations.

Suppose that consequence C represents the successful commission of crimes, behavior B is the act of selectively choosing areas and targets for crime, and tensions T are the characteristics of places that disrupt (or facilitate) C, such as the perceived value of targets and level of controls (e.g., formal police presence, informal intervention by residents). When controls (T) are high or vary across place and time, the successful
commission of crime \((C)\) becomes inconsistent and uneven, therefore forcing offenders to choose carefully the areas and targets for crime \((B)\). As consequences \(C\) become more consistent and it is easier to obtain the intended result (e.g., successful crime), behaviors \(B\) that facilitate the intended consequences (e.g., searching for suitable targets) get weaker—hence the negative effect of \(C\) on \(B\). Higher tensions create more inconsistent consequences, resulting in a greater need to engage in the behaviors that achieve the intended goal. In this example, the mechanisms that explain why some places have more crime than others are (a) the process by which offenders select targets based on the perceived likelihood of successful completion of the crime and (b) the quality, quantity, and influence of tensions that disrupt successful completion of crime sought by offenders.

With few exceptions, most theories in geographic criminology follow this functional causal structure as elaborated next.

![Figure 2.1](image.png)

**Figure 2.1.** The basic causal structure of functional explanations, extended to include sources \((S)\) of tensions \((T)\) and behaviors \((B)\) that are reinforced by the desired consequence \((C)\). Adapted from Stinchcombe (1987).
The key differences among functional explanations of crime are the specific variables that represent \( C \), \( B \), and \( T \) in this causal structure. Table 2.1 cross-classifies many theories according to this scheme. Theories in environmental criminology, including routine activity theory (Cohen & Felson, 1979), crime pattern theory (Brantingham & Brantingham, 1993), place management theory (Eck, 1994; Madensen, 2007), and Cornish and Clarke’s (1985) rational choice model each specify the desired consequence \( C \) as successful completion of crimes such that offenders behave \( B \) in a way that reassures the continued existence of \( C \) like in the hypothetical example of kids breaking into cars. It is the sources of tension \( (T) \) that differ somewhat across these theories. In routine activity theory, the quality or suitability of targets, the capability of guardians, and the supply of these elements in spatial-temporal relation to motivated offenders serve as the main tensions in the system (Cohen & Felson, 1979). In crime pattern theory and the rational choice perspective, environmental cues serve as tensions on the perceived risks and rewards associated with different settings by signaling to offenders whether a given place or target is ‘good’ for crime (Brantingham & Brantingham, 1993; Clarke & Cornish, 1985). Place management theory proposes that individuals invested in the area can supervise the space and maintain order to generate tension (Madensen & Eck, 2013). In each case, certain conditions are selected by offenders for crime more frequently than others because they facilitate the successful completion of crime.

Theories in the social disorganization tradition specify the consequence \( C \) from the community’s point of view as the effective control of crime (Kornhauser, 1978), the behavior \( B \) as the act of intervening to protect the community from criminal activity (e.g.,
collective efficacy), and tension $T$ as influence of criminal motivation and conflict. When criminal activity attempts to gain a foothold in the community ($T$), residents must intervene ($B$) to maintain low levels of crime ($C$) (Sampson et al., 1997).

Table 2.1. Cross classification of theories in geographic criminology using a functional causal structure (see figure 2.1).

<table>
<thead>
<tr>
<th>Theory</th>
<th>$C$</th>
<th>$B$</th>
<th>$T$</th>
<th>$S$</th>
<th>Representative References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social disorganization</td>
<td>Crime free community</td>
<td>Social organization</td>
<td>Criminal motivation</td>
<td>Social structure; conflict</td>
<td>(Shaw &amp; McKay, 1942)</td>
</tr>
<tr>
<td>Systemic model</td>
<td>Crime free community</td>
<td>Willingness to intervene</td>
<td>Criminal motivation</td>
<td>Social ties; social capital; political economy</td>
<td>(Bursik Jr &amp; Grasmick, 1999)</td>
</tr>
<tr>
<td>Collective efficacy</td>
<td>Crime free community</td>
<td>Willingness to intervene</td>
<td>Criminal motivation</td>
<td>Social structure</td>
<td>(Sampson et al., 1997)</td>
</tr>
<tr>
<td>Routine activity theory</td>
<td>Successful completion of crime</td>
<td>Offenders select certain sites/targets</td>
<td>Target suitability; capable guardians; convergence with offenders</td>
<td>Daily routines; socio-economic structure</td>
<td>(Cohen &amp; Felson, 1979)</td>
</tr>
<tr>
<td>Crime pattern theory</td>
<td>Successful completion of crime</td>
<td>Offenders select certain sites/targets</td>
<td>Environmental “cues”</td>
<td>Urban design; nodes, paths, edges</td>
<td>(Brantingham &amp; Brantingham, 1993)</td>
</tr>
<tr>
<td>Rational choice</td>
<td>Successful completion of crime</td>
<td>Offenders select certain sites/targets</td>
<td>Risks; rewards; provocations</td>
<td>Individual differences</td>
<td>(Clarke &amp; Cornish, 1985)</td>
</tr>
</tbody>
</table>
We can easily extend the functional causal structure in figure 2.1.1 to accommodate structural conditions $S$ which determine the quality and quantity of tensions $T$ or behaviors $B$, as shown in figure 2.1.2. This extension is helpful for understanding the distal or indirect forces on $C$ that also represent key differences among theories. For example, social disorganization theories assert that structural conditions ($S$), such as disadvantage and residential instability, determine a neighborhood’s ability to realize informal social control ($B$), which in turn reduces or prevents crime (Shaw & McKay, 1942). In the systemic model, neighborhood characteristics such as social ties and social capital influence the ability to achieve social control (Bursik Jr & Grasmick, 1999). Local institutions (Peterson et al., 2000; Short Jr, 1993; Wilson, 1987), the political economy (Bursik Jr, 1989; Bursik Jr & Grasmick, 1999; Velez, 2001), and formal means such as the police (Skogan & Hartnett, 1997; Trojanowicz & Bucqueroux, 1990) can also serve as key sources of neighborhood social controls (Kubrin & Weitzer, 2003a).

Other theories in community criminology define sources of criminal motivations or conflicts that cause tension in the system ($T$). For example, Anderson’s (1999) code of the street suggests that cultures of violence act as tensions ($T$) and develop in response to structural conditions ($S$). Further, the conduct of formal controls (primarily the police) contribute to feelings of legal cynicism (Sampson & Bartusch, 1998) and perceptions of unfairness and government illegitimacy (Tyler, 1990) which decrease the willingness of people to comply with the law ($S$). This tension on the capacity of a community to control crime ($C$) increases the need for residents’ willingness to intervene ($B$). The ability of a
community to intervene determines whether social control overrules tensions in the system.

Environmental criminology theories also specify structural conditions \((S)\) that are deemed important for the distribution and quality of tensions \((T)\) which force offenders to be selective about the times and places they choose to commit crime \((B)\) such that they are successful in doing so \((C)\). Routine activity theory proposes that everyday activities, like going to work or school, drive the spatial-temporal distribution of targets and guardians which put tension on the system. Cohen and Felson’s (1979) seminal article examined how changes in activities away from the household \((S)\) decreased guardianship at home and increased target availability outside the home \((T)\). In crime pattern theory, urban form is a key determinant \((S)\) of offender activity patterns and the places they select for crime \((B)\), as well as the environmental cues which cause tension \((T)\) on the successful completion of crime. For example, the mixture of residential and commercial land uses create perceptual “edges” in the urban landscape which burglars use to identify crime sites with low risk of being noticed (Brantingham & Brantingham, 1975).

Relatedly, street networks drive the distribution of passersby who may serve as guardians via “eyes on the street” (Jacobs, 1961). For example, guardianship events are more likely to occur on streets that are more central to the transportation network (Birks & Davies, 2017), which could push offenders to other areas where risk of guardianship is lower. Other sources of tension include place management of certain types of land uses, such as a lack of supervision in bar establishments or at certain types of transportation nodes (Eck et al., 2007). At an individual level, the antecedents \((S)\) to selecting suitable places or targets \((B)\) may stem from differences in preferences or psychological traits that
affect decision making (Clarke & Cornish, 1985; Hipp, 2016). The ability for offenders to select low risk, high reward places and targets determines whether their selective abilities can overrule the tensions in the system to successfully complete crimes.

The main takeaway from the above discussion is that although a wide range of variables are used among mainstream theories, most traditional models in criminology rely on a common causal structure which Stinchcombe (1987) describes as “functional.” Because a common causal structure is used, the form that theoretical expectations take is also consistent across suitability theories and testing their propositions is a straightforward enterprise. The researcher simply determines whether the variables proposed by the theory are correlated with the outcome (Stinchcombe, 1987). The biggest challenge is correctly operationalizing the constructs and specifying their relationships to one another and crime outcomes.

Suitability theories can also be easily tested against one another because it is the variables that distinguish them, not the causal structure. All one needs are measures that correspond to different theories, and then one can regress the distribution of crime on the distributions of each independent variable while controlling for potential confounders. The variables with significant effects in the expected direction are deemed positive evidence for the theory they refer to, and variables with nonsignificant effects or those in the unexpected direction are deemed negative evidence for those theories (Stinchcombe, 1987). Consequently, the literature is rich with studies that have refined the relationships and contingencies among the variables that represent the behaviors, consequences, tensions, and sources proposed by a range of criminological theories. Because this proposal is not interested in the effects of particular variables, interested readers are
referred to excellent reviews of the relevant literature pertaining to social disorganization (Bursik Jr, 1988; Kubrin & Weitzer, 2003a), environmental criminology (Andresen, 2014), social networks (Faust & Tita, 2019), situational opportunity theory (Wilcox & Cullen, 2018), offender decision making (Pogarsky et al., 2018), victimization (Lauritsen & Rezey, 2018), macro trends (Baumer et al., 2018), and the criminology of place (Weisburd & Eck, 2018a). Suitability theories have therefore taken the field a long way toward understanding the functional social systems that contribute to the geographic distribution of crime.

One interesting consequence of the causal structure of suitability theories is that they propose one solution to the equilibrium system. If crime is unevenly distributed, so too must be the independent variables of interest. If variable $X$ causes $Y$ to occur, then changes in $X$ should correspond to changes in $Y$ as well. The processes are therefore stationary, even if the effects of variables that make up the process are not. For instance, the effect of collective efficacy on crime is moderated by network interactions within neighborhoods (Browning et al., 2004). The effect of collective efficacy is contingent on other neighborhood factors, but the process of suitability (via social controls) is composed of both collective efficacy and the factors that interact with it (e.g., social ties). The solution to the system does not change, it just requires knowing all the factors involved and their relations within the system.

Further, the factors that make a context “suitable” may be different across place and time, even though the basic theoretical argument and process is the same. For this reason, different theories (variables) may seem to apply in some contexts, but not others. For example, the effect of racial/ethnic heterogeneity was a key variable in Shaw and
McKay’s (1942) explication of social disorganization, but evidence for its positive effect on crime has deteriorated over time (Morenoff et al., 2001; Ousey & Kubrin, 2018). This demonstrates a serious challenge to testing suitability theories, because the observed effects of key variables may often be context-specific or historically contingent. Thus, negative evidence may simply speak to the limited generality of a particular variable, not the invalidity of the underlying suitability process at play. This is perhaps one reason why few theories in criminology have ever been falsified (Bernard, 1990).

**Offender Crime Site Selection**

Many studies of the functional causal structure described above theoretically justify the relationship between crime and place through offender decision making. Some researchers will note the ecological fallacy as one reason why it is difficult to attribute an observed macro-level relationship to micro decision making. Yet, the examples above suggest that each theory relies on the assumption that suitable places are selected by individuals who (rationally) prefer optimal locations to commit their crimes. Certain areas are attractive to potential offenders, drawing them to the area for crime (Brantingham & Brantingham, 1995; Clarke & Cornish, 1985; Felson & Clarke, 1998; Stark, 1987). Empirical evidence for this micro-level decision process includes qualitative accounts from offenders themselves (Rengert & Wasilchick, 1985; Rossmo & Summers, 2019; St. Jean, 2008; Wright & Decker, 1996, 1997), as well as quantitative studies described next.

*Discrete choice modeling.* Bernasco and colleagues have popularized the discrete choice model as one means for examining where offenders choose to commit their crimes
using empirical data (Bernasco, 2010a, 2010b; Bernasco & Block, 2009; Bernasco et al., 2015; Bernasco & Nieuwebeerta, 2004; Lammers et al., 2015; Townsley et al., 2016). The discrete choice model will be described in detail in Chapter 4, but the findings from this line of research are consistent with the propositions of environmental criminology and mainstream suitability theory that offenders rely on measurable place characteristics to select where to commit crimes (Johnson & Summers, 2015).

One important contribution from discrete choice modeling is the observation that individual-specific factors have explanatory power. Bernasco and Block (2009) found that place characteristics of crime sites and characteristics of offenders’ residents interact in crime site selection. For example, a large dissimilarity between the racial composition of an offender’s home neighborhood and the racial composition of potential crime sites is negatively related to selecting that place for crime. This finding demonstrates the role of social barriers that make areas less likely to be chosen if the offender feels like an outsider (Bernasco & Block, 2009). In this way, the joint composition of home and crime site neighborhoods is dependent upon which offender is under consideration. A given neighborhood may be preferable to one offender due to the specific place characteristics there, but not preferred by another. To use another example, Bernasco (2010b) found that offenders often return to areas near places where they previously lived, an individual-specific neighborhood quality that is inconsequential for other offenders. This has been extended to include the residential neighborhoods of offenders’ family members, which are also desirable places for offending (Menting et al., 2016). Furthermore, other research shows preference variation among offenders regarding the influence of suitability factors (Townsley et al., 2016). These findings reflect the need to think more carefully about the
link between place suitability and crime patterns (link 4 in figure 2.2), because the same place factors can mean different things for different offenders. Yet, the researchers still do not question whether place effects are crucial in offender decision making.

Agent-based modeling. A second means for examining offender location involves simulation in a controlled environment using agent-based models (Groff, 2007). An advantage to agent-based models is the ability to examine how micro decision making generates aggregate patterns (Epstein & Axtell, 1996). Studies using this approach have found evidence for a variety of place-based effects. Birks and Davies (2017) examine the role of street network configurations on crime by demonstrating how street closures both decrease offender access to targets but also decrease guardianship. Groff (2007) shows that when people spend more time away from home, aggregate patterns of robbery will be affected because of (perceived) changes in guardianship and suitable target availability. Malleson et al. (2013) demonstrate how an urban regeneration project could reduce burglary in target sites by increasing collective efficacy and household security. These examples further demonstrate the role of the macro-suitability context on crime, through offender decision making (see Groff et al., 2019 for a thorough review of agent-based models in criminology). A key assumption made across these studies is that offenders respond rationally to situational factors that contribute to crime suitability.

Composite Suitability Concept

This chapter has argued that mainstream criminological theories rely on an assumption that crimes occur in suitable contexts. As it pertains to the geography of
crime, it is assumed that offenders search for suitable locations to commit their crimes.\(^1\) Crime and place research identifies a large number of candidate suitability factors. Given that each theory follows a similar causal structure with the suitability assumption, it follows that all place suitability factors can be theoretically combined into a composite concept representing influence from many sources simultaneously.

We can imagine locational suitability as an “\(n\)-dimensional hypervolume,” defined by \(n\) independent axes which make up all possible environmental configurations. Each axis in the hypervolume represents a unique place characteristic that relates with crime, such as social control, target availability, or any other possible sources or tensions that comprise the functional crime causal structure (see table 2.1). Across all the possible configurations which exist in the \(n\)-dimensional space, crime is expected to occupy the region where values of each axis are optimal for criminal behavior.

Figure 2.2 illustrates this idea, adapting Hutchinson’s (1978) conceptualization, for the case of \(n=3\) suitability factors.\(^2\) The \(n=3\) case is presented for illustration, but any number of factors could be conceptualized. The ideal combination of suitability factors for crime to be committed is represented as a box in the diagram, and most crimes (shown as red points in Figure 2.2.2) will occur within this zone of suitability. The box occupies the space among the three factors where disadvantage is high, collective efficacy is low, and the number of people present in the area is a balance between a

\(^{1}\) Although not elaborated in this dissertation, it could be argued that the crime suitability perspective dominates all subfields in criminology. Future work should extend the historicist viewpoint (discussed in Chapter 3) beyond geographic criminology.

sufficient number of targets but not too many people such that guardianship is high (Birks & Davies, 2017).

The hypervolume concept is derived from an idea proposed by Hutchinson (1957); (Hutchinson, 1978) in regard to ecological niches, which Felson (2006) repurposed to describe crime niches. He defines the crime niche as consisting of “all aspects of a crime’s existence that enable it to survive and grow” (Felson, 2006, p. 125). In the geographic context, place suitability factors provide these criminological necessities that must co-occur in space in time for crime to occur (Cohen & Felson, 1979). In slightly more formal terms, the hypervolume function $h(x)$ maps an $n$-dimensional Euclidean space onto a 1-dimensional Euclidean space (Blonder, 2018) so that a single value of crime suitability can be conceptualized and measured for any given place. This idea resembles the use of ordination techniques such as principal components factor analysis to combine several measures into a combined metric. Alternatively, we can imagine the mapping function as a linear equation with $n$ variables which produces a 1-dimensional crime prediction line. If the mapping function is purely theoretical we can assume it has little or no error, whereas empirical functions (via regression estimates, for example) are likely to have more error from omitted variables and measurement error. From the criminological literature, crime suitability is akin to results from risk terrain mapping techniques used to predict crime from environmental variables (Caplan et al., 2011).
Crime suitability conceptualized as a $n$-dimensional space with regard to $n=3$ place factors, which can be combined into a composite metric. Suitability for crime is highest within the box, where disadvantage is high, collective efficacy is low, and the number of people present is a balance between a large number of targets but not too many guardians.

Figure 2.2 is represented as the general case, but crime type-specific examples could be proposed. For example, the ideal conditions for commercial burglary would include few or no people present in the area, whereas street robbery or pick-pocketing would require a greater number of passersby (Clarke, 1995; Cornish & Clarke, 1986; Felson & Clarke, 1998). These differences could be visualized by making the points in figure 2.2 colored according to offense type and identifying the regions where points of
the same color cluster together, which would represent the ideal conditions for that type of crime. Various analytic methods for examining the overlap (or lack thereof) of crime type-specific suitability exist in the literature (e.g., see Andresen, 2007; Brantingham, 2016; Brantingham & Brantingham, 1998; Quick et al., 2018; Wheeler et al., 2018), but further exploration is beyond the goals of this dissertation. The general case is sufficient for understanding how suitability is conceptualized as a composite concept, representing the combined influence from many place factors necessary for crime. This concept can now be applied to understand the connection between offender decision making and aggregate crime patterns, as proposed in mainstream theory.

Micro-macro Causal Structure

This chapter has discussed the relationship between crime and place without explicitly dealing with scale. Issues related to the scale of inquiry are well known in criminology (Hipp & Williams, 2020; Matsueda, 2017; Mohler et al., 2018; Short Jr, 1989, 1998; Taylor, 2015). Social science more broadly has a long history of discussing relationships between levels of analysis, most notably the work of Coleman (1968, 1986, 1990). Following this tradition of scholarship, figure 2.3 illustrates the micro-macro process that relates locational suitability to aggregate crime patterns. Link 1 represents the offender decision to commit a crime at a preferred location. Mainstream theory assumes that location preferences are determined by suitability factors perceived in the environment through link 2. In crime pattern theory, for example, Brantingham and Brantingham (1993) hypothesize that offenders perceive “cues” emitted by the environment. Offenders learn through experience which cues are associated with ‘good’
places for committing crime. This learning process creates behavioral templates that help them assess situations during future target searches (Brantingham & Brantingham, 1981, 1984). Consistent with the functional causal structure, offenders will update their locational preferences based on the consequences of selecting a given location for crime (Clarke & Cornish, 1985). If the crime is successful (e.g., high reward, no punishment), the environmental conditions will be favored in the future; if the crime is not successful, those environmental conditions will tend to be avoided. Crime location choices should, on average across all crime events, covary with location suitability, and any “errors” made by offenders who commit crimes in unsuitable places will be corrected and averaged out over time.

Figure 2.3. Micro-macro causal structure of mainstream suitability theory in geographic criminology.
Link 3 in the micro-macro causal structure represents the aggregation of each offender’s location choices. Suitability theories assume that offenders have uniform preferences and a strong ability to correctly perceive environmental cues that reflect suitability. Under these assumptions, the sum of crime location choices should reflect suitability conditions. This is implied by link 4 in figure 2.3. It follows that links 1 through 3 are subsumed by link 4 (Kincaid, 1996). It also follows that locational suitability effects can be tested by demonstrating that suitability conditions covary with crime patterns (link 5), implying that links 1 through 3 exist. This is generally the approach of testing mainstream suitability theories at the aggregate level in geographic criminology.

**Conclusion**

This chapter generalized the theoretical propositions of mainstream theories intending to explain geographic patterns of crime. It was argued that all such theories utilize a functional causal structure, whereby according to Stinchcombe (1987), the consequences of a behavior become its causes. As it relates to crime, offenders select certain places for crime because crimes committed in that location are considered successful. In other words, certain characteristics of that place function to make it suitable for committing crime. A large number of characteristics have been hypothesized and examined in the literature using a variety of methods. All theoretically plausible suitability factors can be represented as an $n$-dimensional hypervolume as a composite metric for place suitability.
Scientific knowledge about the relationship between crime and place continues to grow, but the field lacks theoretical viewpoints which challenge the underlying causal structure of mainstream suitability theories. Path dependence represents an alternative ‘historicist’ causal structure that will be described in the next chapter. A more thorough consideration of alternative processes, such as path dependence, are crucial to developing a more complete understanding of criminological processes, their consequences, and the implications for crime policy.
Chapter 3. Path Dependence Theory

The goal of this dissertation is to examine an undertheorized path dependence mechanism that has important implications for crime theory and policy. In short, my argument states that offenders choose where to commit their crimes on the basis of history, specifically selecting places where they or their co-offenders have committed crimes in the past. This is explained as a status quo bias in decision making. These biased decisions are made at the micro level but have significant consequences for aggregate crime patterns by generating nonlinear feedback effects. Continually re-selecting previous crime sites results in spatial clustering of crimes. Furthermore, path dependence implies a weakening of location suitability effects. Although the extreme scenario where place has null effects is unlikely to fit reality, my contention is that history can substantially influence crime patterns even if it is not all-powerful. The compounding influence of history can make it difficult to reverse an entrenched crime problem that has become “locked-in.” The remainder of this chapter explains this “history matters” viewpoint in greater detail and provides testable hypotheses to be examined in subsequent chapters.

Path Dependence Processes

Path dependence is a general class of processes defined by positive feedback and self-reinforcing change. Path dependence is explained as a “foundational concept” (David, 2007) because it can characterize a wide range of social phenomena. Widespread attention has been given to this kind of process in the social sciences. Examples include applications in economics (Arthur, 1990a, 1994), political science (Pierson, 2000, 2004),
historical sociology (Mahoney, 2000), economic geography (Dumais et al., 2002; Fujita &Thisse, 1996; Krugman, 1991; Martin & Sunley, 2006), institutional theory (North, 1991), urban planning (Arthur, 1988b), and many others.

Consider the computer (typewriter) keyboard as an illustrating example. Without knowing its history, is there a straightforward explanation for the specific configuration of keys, with letters beginning in the top-left corner with “QWERTY”? Is there not a more efficient configuration possible? Was this option supremely optimal and destined to dominate computer keyboards eventually? Or was the QWERTY keyboard used early-on, making it more advantageous to follow the status quo and continue producing QWERTY keyboards rather than to introduce an alternative? David (1985) suggested the latter explanation, which has become the classic example of path dependence in the social sciences. The question of computer keyboards is trivial, but it begs questions about other areas of social life where behavior is locked-in to potentially inferior outcomes. Arthur (1989) suggested decades ago that empirical examples could be identified in the economy, whereby early-established options become dominant and could prevent superior alternatives from succeeding. Why did so many technology companies locate in Silicon Valley rather than another location (Arthur, 1990b)? Why did VHS tapes come to dominate the VCR market, especially if it were true that Beta was an equivalent (or even superior) product (Arthur, 1994)? Why did we settle on gasoline locomotion automobiles over steam locomotion (Arthur, 1990a)? These pioneering observations began a scientific literature to understand why economies can become locked-in to an outcome, despite the possibility of more efficient alternatives. A primary goal of these researchers was to
determine the conditions under which historical chance can influence economic outcomes.

A classic demonstration of path dependence is the urn model (Arthur et al., 1983, 1987). Suppose you have a large urn that has one white ball and one red ball inside. Now suppose you randomly select one ball and return it to the urn with an additional ball of the same color. This process is repeated many times until the urn is full. With each draw, the probability of selecting a red ball changes, because adding one additional ball of the same color changes the relative frequency of red and white balls. Early draws in the sequence have a large influence on the color distribution. Each additional ball, however, has decreasing influence on the frequency of each color as the number of balls in the urn increases. Eventually, the distribution becomes locked-in and additional draws exert very little influence on subsequent draws because the proportions are affected relatively insignificantly. The final relative frequency of red to white balls is unpredictable from the outset and ignores any sort of initial color advantages. Early draws exert a large amount of influence on the proportions that eventually become stable and locked-in. Once locked-in, changing the proportions is unlikely.

The urn model exemplifies several distinctive features of path dependence (Arthur, 1994). First, path dependent systems are unpredictable, having many possible outcomes or stable equilibrium points. The urn could have been filled with any combination of red and white balls. The specific outcome that occurs is contingent upon early chance events that select one of many possible paths. Second, the specific path chosen can become ‘locked-in,’ meaning that reversing course or switching paths is increasingly difficult. Once the ratio of red to white balls reached a certain point, the ratio
did not change much thereafter and adding more balls had little effect on the composition. Third, path dependent systems are nonergodic or highly contingent, referring to the importance of seemingly ‘small’ events that determine the outcome and cannot be ignored as noise or ‘averaged out.’ Timing is key because an early event can exert large influence on the outcome, even if that same event would be relatively insignificant if it had occurred later in the sequence. Finally, path dependent systems are potentially path inefficient. This is not obvious from the urn model because path dependence ignores efficiency. This means that an established outcome may generate lower payoffs or benefits than foregone alternatives. This is interesting because the most suitable or optimal options may not be selected, despite their advantages over alternatives.

Path dependence processes follow the ‘historicist’ causal structure described by Stinchcombe (1987). *Historicist explanations* suggest that “an effect created by causes at some previous period becomes a cause of that same effect in succeeding periods” (Stinchcombe, 1987, p. 103). The basic causal structure is illustrated in figure 3.1 The point at ‘x’ is an initial cause of y and D stands for a temporal delay that implies y acts as a cause in the following time period. The P refers to the path dependent mechanism that self-reinforces y. Stinchcombe (1987) suggests that D and P give historicist explanations their distinctive character and carry the greatest amount of theoretical importance.
Figure 3.1. Elementary structure of historicist explanations. Adapted from Stinchcombe (1987).

The key theoretical question, then, concerns the mechanisms that explain how positive feedback is generated and maintained. Social theorists have identified many different mechanisms to explain examples of “increasing returns” or positive feedback in their respective fields. In economics, Arthur (1994) argues path dependence is driven by:

1. large set-up or fixed costs that provide financial incentives to stay with the same product;
2. learning effects that increase innovation and efficiency with continued use;
3. coordination effects that occur when a product becomes more attractive as more people use it, and;
4. adaptive expectations that make individuals want to choose the option that will dominate the market later and thereby follow a self-fulfilling prophecy.

When an economy is characterized by these properties, such as in many technology industries (e.g., think iPhone versus Android), path dependence can drive the dynamics to select which product or service monopolizes the market.

Pierson (2004) revised the potential economic mechanisms to explain why path dependence is important in political life. Politics differs from economics but has its own
set of features that are conducive to positive feedback. These include the central role of collective action in politics, high institution density, the use of political authority for increasing power asymmetry, and intrinsic complexity and opacity of the political world. These features, Pierson (2004) argues, make path dependence prevalent in politics.

Criminological behavior shares many features with economics and politics which increase the potential for path dependence to drive crime patterns. As in economics, engaging in crime can involve large set up costs in the form of investing time into learning how to commit crimes effectively. Once learned, however, efficiency is increased as more crimes are committed and the offender develops a specific modus operandi (Bouhana et al., 2016; Rossmo, 1999). As in politics, crime is a collective behavior often involving co-offenders whose behavior tends to become more attractive to their peers (Akers, 1973; Sutherland et al., 1992; Warr, 2002). At the same time, co-offending groups are dynamic and unorganized (Klein, 1997; Klein & Maxson, 2010), minimizing the ability for a centralized trial-and-error mechanism to funnel offenders towards the most optimal behaviors.

But these are only characteristics that describe how path dependence processes might operate. What is missing is a specific mechanism explaining why features like collective action generate positive feedback. To this end, the next section describes work in behavioral economics to provide a critical set of theory and research findings on individual-level decision making that is relevant in understanding path dependence. I argue that connecting aggregate crime patterns to microscopic decision making is central to developing a more complete theoretical understanding from the bottom up.
Theories of Decision Making

Conventional, “neoclassical” economic theories rely on the assumption that the rational utility model (Von Neumann & Morgenstern, 1944) accurately describes how people make decisions. This model holds that individuals have clear, stable preferences that are reflected in their choices. If preferences are known, then choices are predictable. Empirical results are considered anomalies if one cannot identify a “rational” reason for the choice, and such anomalies can be ignored as noise. Neoclassical economic theory therefore claims to describe not only how people should make decisions (i.e., to maximize utility), but also how people make decisions in practice. Thaler (1980) suggested that the rational choice model was not a good description of actual consumer behavior and therefore should be modified to better predict how people will behave in real life. The anomalies that were once ignored as noise became the focus of investigation (Kahneman et al., 1991; Lewis, 2016; Thaler, 2015).

Examining these deviations from the rational utility model resulted in modifications to understanding how people make choices. Most relevant to the present work is a phenomenon characterized in multiple ways as the endowment effect (Thaler, 1980), status quo bias (Samuelson & Zeckhauser, 1988), and loss aversion (Tversky & Kahneman, 1991). These concepts similarly describe how people select options with respect to an assumed reference point (Kahneman & Tversky, 1984). In summary, losses are weighted more heavily than gains so that individuals are more likely to forego a potential gain than accept a loss of the same value.

The preferential difference between gains and losses exemplifies the importance of the reference point or how the decision is framed (Kahneman & Tversky, 1984). The
endowment effect, for example, suggests that the $50 in one’s pocket (i.e., in the “endowment”) is valued more than the potential to add $50 to one’s pocket. Under the rational choice model, losing $50 is economically equal to losing the opportunity to receive another $50, yet people do not evaluate these alternatives equally. The subjective value difference (i.e., keeping $50 > receiving $50) exists because keeping something is viewed as averting a loss, whereas receiving something is viewed as a gain (Thaler, 1980). It simply feels worse to ‘lose’ than to ‘not gain.’ The difference lies in how framing changes the perceived values of alternatives (Kahneman & Tversky, 1984).

Individuals are risk averse or tend to avoid situations where they stand to lose something. Loss aversion can be generalized when framed as a bias towards the status quo. Samuelson and Zeckhauser (1988) state the following in their seminal article on the topic:

Doing nothing or maintaining one’s current or previous decision is almost always a possibility. Faced with new options, decision makers often stick with the status quo alternative, for example, to follow customary company policy, to elect an incumbent to still another term in office, to purchase the same product brands, or to stay in the same job (Samuelson & Zeckhauser, 1988, p. 8).

The tendency to stick with the status quo option can be explained as loss aversion. When faced with a decision to retain the status quo or opt for a new alternative, the status quo becomes the reference point against which all options in a decision are compared. The potential losses from switching to a new option are weighted more heavily than the potential gains of switching, leading decision makers to retain the status quo (Samuelson & Zeckhauser, 1988).
Samuelson and Zeckhauser (1988) described other explanations for the observed status quo bias. Another explanation involves psychological commitments and the idea of *sunk costs* (Brockner & Rubin, 1985). Individuals may be seeking to justify a previous commitment by repeating the same choice. For instance, paying for major engine repairs on a vehicle that has already costed thousands of dollars in minor repairs. The previous costs are viewed as “sunk” and therefore irrelevant to the decision to repair the engine or purchase a new vehicle. Now that the individual has already invested financially in the vehicle, they are committed to keeping it around. They may also be following through on a psychological investment in their choice. Schoenberger (1979) provides a high-stakes example when he suggests that President Truman decided to use atomic weapons in World War II to justify the billion dollars spent in the Manhattan Project. These scenarios exemplify psychological commitments that may steer individuals towards the status quo.

Greater investments in an option yield stronger commitments to retain it.

The loss aversion and psychological commitment explanations for status quo bias are at odds with the neoclassical rational utility model. But re-selecting the same option can, in some cases, be rational. Samuelson and Zeckhauser (1988) suggest that it could simply reflect preference for the optimal choice in two independent decisions. Assuming that the objective utility of the choices is the same in both decisions, the rational individual should select the same optimal option each time. Selecting a different option is an error, and over many decisions the ‘best’ alternative should be the average choice. Additionally, switching to a new alternative could involve transition costs, thereby making it rational to stick with the status quo option. Searching for and analyzing new alternatives comes at a cost and may outweigh potential gains associated with switching.
For these reasons, re-selecting the status quo may not be a bias but instead a reflection of the best choice. Of course, the rational explanations are designed out of the cited experiments, providing evidence for the status quo *bias*.

Bias towards status quo options applies in a variety of decision making contexts. Anecdotally, consider many of the choices we make in our everyday lives about where to shop for groceries, which restaurants to patronize, where to get a haircut, and which vehicle to purchase. Do most people search for the ‘best’ grocery store, summing the cost of each item they plan to purchase, sifting through coupon ads, and considering travel costs before deciding where to shop? If this process is undertaken, do they recalculate expected utilities each time they need groceries? Or do most people tend to shop at the same grocery store habitually, assuming they will successfully acquire what they need if they go back to the same place? The latter is more likely and the same is probably true for many activities. The status quo option seems safe. Research shows that companies are more successful when they have greater brand consistency and product similarity when they extend their offerings (Park et al., 1991). Consumers react more favorably to the same, safe options and less favorably towards options that are new and different.

A central argument in this dissertation is that crime location choice, like in other decision contexts, is heavily influenced by status quo bias. When this bias is combined with other criminological processes such as co-offender influence, path dependence is prevalent. The remaining sections in this chapter explain status quo bias in offender decision making and how it generates positive feedback in aggregate crime patterns.
Status Quo Bias in Crime Site Selection

Empirical evidence shows that offenders are more likely to offend in previous crime sites than other sites. Bernasco et al. (2015) found that the odds burglars re-selected the same area for crime were between 2 and 16 times higher than the odds of selecting other areas, depending on how recently the previous burglary at the location was committed. Lammers et al. (2015) similarly found that the odds of repeating crime of any type in the same area were seven times higher than the odds of committing the crime elsewhere. These studies demonstrate that offenders are likely to select the status quo option.

From the perspective of mainstream theory, offenders return to crime sites that they learn are suitable for crime (Bernasco et al., 2015; Lammers et al., 2015). This interpretation mirrors neoclassical economics, suggesting that re-selected crime sites are suitable (optimal) and therefore more likely to be chosen. Once selected for crime, offenders confirm their suspicions that it is indeed a good location and return again in future crimes.

My contention parallels that of the behavioral economists’ that, while the crime suitability model of mainstream theory may represent how offenders should select crime sites to produce ‘optimal’ outcomes, it should be modified to better fit how those decisions are actually made. I claim that re-selecting a location for crime may occur even if alternative sites are more suitable. Previous crime locations represent status quo options that serve as the reference point for alternative options. The status quo option is

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3 In both studies, the odds of returning to previous crime sites were increased with recency to the prior event, meaning that committing a crime there in the previous week had greater effect than if the previous crime was committed last year. Crime site re-selection was more likely if the crime was of the same type as the past crime and if the offender had committed crimes there more frequently.
expected to yield a successful crime just as it has in the past. Selecting a new location risks losing out on that expectation. Other sites may be better options and have a potential for gain. But potential losses weigh heavier than potential gains (Kahneman et al., 1991; Kahneman & Tversky, 1984; Thaler, 1980; Tversky & Kahneman, 1991). The offender is more likely to avert loss by re-selecting the tried-and-true status quo location.

Two alternative explanations explain the same pattern of behavior. Yet, the mainstream theory interpretation is somewhat at odds with an important piece of the evidence. The aforementioned studies control for a large number of hypothesized place suitability factors (e.g., socio-demographics, risky facilities). Suitability theory should expect the effect of prior crime site to be absorbed by the effects of known place covariates. If offender decisions are based supremely on locational suitability, prior crime locations should be confounded with suitability variables. This is not the case. While these characteristics remain significant in the models, the status quo effects are independent of suitability and are arguably larger in magnitude. Re-selecting the status quo does not appear to be the optimal option, but rather a bias that detracts offenders from more suitable options.

Status quo bias in this context, like in behavioral economics, can be explained as a consequence of loss aversion. When a first-time offender commits a crime, the status quo option is then set to be the location of that crime. The crime occurred, implying it was “successful.” Suppose now the offender decides to commit a second crime. Historically, the status quo option (i.e., the previous crime location) resulted in a successful crime, so subsequent crimes at that location are expected to be successful too. Attempting crime at a new location risks losing what the offender perceives to be inevitable or guaranteed,
given their past success. The individual discounts what could be gained in a new location (higher value targets, lower guardianship) and greatly values what stands to be lost. Framed in terms of losses, the offender is more likely to avert risks of switching and re-select the same location again, than they are to risk loss and try a new location.

Status quo bias is consistent with other known criminological themes. Offenders tend to be impulsive (Gottfredson & Hirschi, 1990; Grasmick et al., 1993; Lynam & Miller, 2004) and therefore more likely to use convenient heuristics when making quick and imprudent decisions. Tversky and Kahneman (1974) argue that “people rely on a limited number of heuristic principles which reduce the complex tasks of assessing probabilities and predicting values to simpler judgmental operations” (p. 1124). It is simpler to return to a prior crime site, than it is to go through the complex task of assessing suitability of a new area.

Secondly, motivation to engage in crime in the first place is often framed in terms of losses from a variety of theoretical viewpoints. Crime is often rooted in maintenance of one’s identity. Violence and other forms of aggression have been identified as identity management tools and a way to “save face” in social interactions (Felson, 1978, 1982; Felson & Steadman, 1983). Maintaining a criminal identity in certain inner-city contexts can be perceived as necessary for survival (Anderson, 1999). Similarly, popularity among peers can have a positive association with delinquency (Felson & Haynie, 2002) which could indicate a perceived fear of losing social status and greater pressure to engage in delinquency.

Strain theories also frame criminal motivation in terms of loss. Agnew (1992) describes how motivation to offend results when an individual stands to lose something
of value, such as achieving one’s goals or acquiring valuable stimuli. Relatedly, a
criminal act can be desirable in and of itself. Katz (1988) hypothesizes the provocative
viewpoint that crime is “enchanted” and can put the offender in a state of “euphoria.”
Wright and Decker (1996) discuss how burglars in their sample experienced “intense
emotions of elation” following the crime. One burglar stated “But uh, it feels good, I’m a
tell you, if you get it and get away with it. It feels good! More excitin’ than ‘Nam [and]
Vietnam was real excitin’” (p. 161). The ability to acquire this feeling by committing
crime may frame the associated decisions in terms of losing an opportunity to experience
pleasure.

Thus, most criminological theories frame the decision to engage in crime in terms
of losses. It follows that decisions of how to engage in crime (e.g., when, where) are
similarly framed in terms of losses. That is to say that failure to complete the crime that
an individual is motivated to commit is interpreted as a loss. Findings from behavioral
economics imply, then, that offenders are likely to be loss averse when deciding where to
commit crime and are therefore subject to bias towards status quo options. The status quo
option offers expectations of repeating success, as compared to alternatives characterized
by risk of loss.

**Co-offenders and Status Quo**

There are two primary sources of status quo in crime location choice. The first is
an offender’s own offending history. Any place where an offender has previously
committed crime in the past is considered a status quo option. The second is the
offending history of one’s co-offenders. Any place where one’s co-offenders have
previously commit crime are also considered status quo options. But this co-offender effect requires additional elaboration.

The importance of co-offender networks is well-known in the criminological literature. Co-offenders provide access to criminal opportunities and can even increase one’s risk of being victimized. An individual’s co-offenders also influence their decision making in myriad ways, including motivation to commit crime and the types of crime that the individual commits. It follows that co-offenders have an effect on where an individual chooses to commit crime.

The status quo of an individual offender is set through experience of committing a crime. It follows that the experiences of one’s co-offenders may also set status quo options in others. The ways this might occur are numerous. One way to think of this process is a parallel to direct and indirect experiences that influence deterrence. Stafford and Warr (1993) discuss how offenders can be deterred by experiencing punishment themselves or through indirectly experiencing punishment through others. Just as punishment experiences can affect other offenders, positive crime experiences in a location may also be transmitted. These experiences may be direct when an individual is present at the time someone in their co-offending network commit a crime. They may also hear of the experience directly from the co-offender. As narrative criminologists are well aware, individuals are often willing to share rich details of their offending experiences and it is likely they do this with their co-offenders as well. Relatedly, transmitting knowledge of one’s past crime locations could result from a sort of tutelage or teaching others about how to successfully commit crime. Finally, knowledge of others’

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4 If the individual is involved in the crime with the co-offender, of course, then this is part of their own offending history as well.
experiences may spread through crime networks just knowledge spread through any social network (Fritsch & Kauffeld-Monz, 2010). Offenders themselves have described this process as “receiving a tip” (Wright & Decker, 1996, pp. 73-77).

**Microscopic Implications**

At the individual level, status quo bias causes offenders to repeatedly select the same sites for crime. They may also re-select sites of their co-offenders. These effects do not apply to first-time offenders who are not embedded in a group of other offenders who may yield status quo options. But first-time offenders may be heavily influenced by co-offender history effects because they do not have their own experiences to guide behavior. But once an individual begins to commit crimes, the status quo bias will establish predictable patterns of behavior. This is perhaps one reason why geographic profiling has been a useful tactic for police investigation (Rossmo, 1999).

Status quo options may be more influential in some circumstances than others. In general, status quo options are expected to have stronger effects when they are nearer to the offender. By “nearer,” I mean that the previous crime location was selected more recently, the crime was experienced directly by the offender rather than indirectly, and the previous event involved the same type of behavior (offense type). These hypotheses are based on psychological processes associated with cognition and memory. Crimes that occurred more distantly in the past are less likely to influence current decisions simply because the individual could have forgotten about them. Alternatively, it is possible that an individual does not hold the same expectation that crime will be successful in the same

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5 Note that this is a tendency to re-select, meaning that more than one location may become a viable status quo option.
location if they think conditions may be different. Some evidence has been found for a temporal decay function of status quo bias (Bernasco et al., 2015; Lammers et al., 2015).

Secondly, offenders are more likely to be influenced by direct experience than indirect experience. Direct experience would include their own offending history or witnessing a crime committed by another. Indirect experience would include any vicarious experience that is transmitted to the individual from another. Direct experiences are known to predict behavior better than indirect experiences (Fazio & Zanna, 1978; Fazio et al., 1978; Zanna & Fazio, 1981). This is because direct experience generates more powerful associations between attitudes and how one evaluates a given choice (Fazio et al., 1989). These associations are stronger because direct experiences are more accessible from memory (Fazio, 1990) and thus more likely to drive behavior (Fazio et al., 1989; Fazio et al., 1986).

Finally, status quo options are more influential when the previous experienced involved a behavior of the same type – in this case, the same offense type. This is demonstrated in prior research of crime location choice (Lammers et al., 2015). It is also intuitive, given that status quo options reference a given behavior. Although crime is one general class of activities, experiences associated with different types of crimes (e.g., homicide versus pickpocketing) are likely to be compartmentalized in memory.

**Path Dependence Model of Crime Location Choice**

The status quo bias discussed above provides a theoretical foundation for path dependence in aggregate crime patterns. To re-iterate, path dependence is characterized by positive feedback and self-reinforcing change over time.
The theoretical model asserts that the re-selection tendencies of individual offenders interact to generate macroscopic patterns of crime that are more concentrated and more resistant to change than if status quo biases were not at play.

These hypotheses are bore out in Figure 3.2 which re-creates the micro-macro causal structure presented in the previous chapter. Once again the crime location choices of offenders are determined by their preferences in link 1. Locational suitability remains a determinant to preferences through link 2, and crime patterns are aggregations of location choices through link 3. Status quo bias is represented by link 5. The backward direction of the arrow represents positive feedback and the self-reinforcing loop generated by re-selection of status quo options. In the case an individual’s offending history, link 5 is expected to have strong influence crime location preferences of that offender. Its effect on aggregate crime patterns through link 3 will vary with the rate at which a given offender commits crime. In terms of the individual offending history effect, a previous crime can affect only those crimes committed by the offender thereafter. Low rate offenders may only commit a handful of crimes and thereby contribute just a handful to the aggregate pattern. Positive feedbacks on high rate offenders will be more consequential, but perhaps still relatively minor in the aggregate if the effect is contained to the individual.
Major influence is generated from status quo bias via network effects. Offending history effects are multiplied when they have potential to influence additional offenders, and the multiplication is increased with the size of the co-offending group. Consider a co-offending group with three individuals, each of which will engage in five crimes. The first crime committed by an individual in the group has the potential to influence the remaining four crimes by the individual offender, and 14 future crimes committed by the group. Already we can see how link 5 in Figure 3.2 is multiplicative. Now consider a co-offending group of 30 individuals who will each commit five crimes. The first crime committed influences the remaining four crimes by the individual and 150 crimes committed by the group (30 individuals × 5 crimes each − 1). This shows quite simply how positive feedback can have major effects on aggregate outcomes if its range increases to other offenders.
A few important things should be noted about the above examples. Note first that each crime committed in the sequence will have decreasing influence on subsequent crimes. In the second scenario, the second crime committed by a member of the group (suppose it is the same individual as the first crime) can influence three remaining crimes by the individual and 149 crimes to be committed by the group. Each additional crime has less impact on the final outcome because fewer events can be influenced. This is consistent with path dependence theory that later events would have greater influence on outcomes if the same event had occurred earlier in the sequence (Arthur, 1994).

Secondly, note that nonlinearity is generated by re-selection tendencies. Recall from behavioral economics that psychological commitments to a choice increase with greater investment (Samuelson & Zeckhauser, 1988). This contextualizes the result from urn theory that selection of an option can increase exponentially until a certain point when the patterns become locked-in.

Lastly, note the nested structure of the processes that have been described. This point foreshadows a neat conceptual model that I will describe later. But note now how status quo options set by an individual’s offending history feedback into that individual’s choices, and the status quo options set by co-offenders feedback into the choices of all individuals in the group. This “nested-ness” will become important later when prescribing various crime reduction policies implied by these theorized feedback loops.

**Other Positive Feedbacks in Crime**

Up to this point I have neglected to discuss a substantial body of criminological research on other sources of positive feedback in crime. The idea that crime can act as its
own cause in the future is not entirely new in the criminological literature. If path
dependence is viewed broadly as a positive feedback process, one could argue that
criminologists have already considered its role in crime. At the individual level, Nagin
and Paternoster (1991, 2000) introduced the state dependence hypothesis to explain the
positive relationship between past and future offending behavior (also see Nagin &
Farrington, 1992). Initially referencing Heckman (1981) they highlight the two basic
processes of population heterogeneity and state dependence as alternative explanations.
Population heterogeneity suggests that an underlying propensity towards deviance
explains why certain individuals repeatedly engage in offending behavior. The general
theory of crime (Gottfredson & Hirschi, 1990), Hirschi’s (1969) social bond theory,
Agnew’s (1992) strain theory, and social learning-type theories (Akers, 1973; Sutherland
et al., 1992) represent the former viewpoint because not all individuals have the same
initial likelihood of engaging in crime which continues to increase risk into the future.

By contrast, state dependence suggests that the act of engaging in deviance alters
individual preferences or constraints that make future offending more likely. The
individual-level state dependence perspective represents a kind of historicist explanation
by asserting that events can change one’s circumstances in a way that increases the
likelihood of those events repeating in the future. Recalling Stinchcombe (1987), the
criminological effect (i.e., engaging in crime) of some individual characteristic or
circumstance was created by that same effect (engaging in crime) in a previous time
period. For example, Sampson and Laub (1995) explain how engaging in deviant
behavior decreases sources of social control in the individual’s life (e.g., loss of
employment, divorce) which in turn increases the likelihood of future offending. The
effect of committing crime therefore feeds back through the context of the individual’s life to increase their risk of offending again. A similar explanation is given to explain repeat victimization; being victimized makes a target more vulnerable for future victimization because being victimized makes them appear more vulnerable (Lauritsen & Quinet, 1995; Tseloni & Pease, 2003, 2004).

The state dependence perspective has also been used to understand the geography of crime (although not under this term). The occurrence of crime is believed to have negative effects on social conditions in the area. As crime problems grow, the area deteriorates, resident fear increases, willingness to exert social control decreases, businesses close, and people move away (Bursik Jr, 1988; Hipp, 2010; Hipp et al., 2009; Hipp & Wickes, 2017; Skogan, 1986, 1992). Consequently, the lack of social control and presence of crime and disorder are cues to offenders that crime is acceptable behavior (Keizer et al., 2008; St. Jean, 2008; Wilson & Kelling, 1982). Crime contributes to the conditions that make it more likely, thereby resulting in a “spiral of decay” (Skogan, 1992).

It is clear that the state dependence perspective is a kind of historicist explanation and can therefore be viewed as a type of positive feedback process. The difference between this and the kind of path dependence mechanisms introduced in this dissertation is that state dependence appeals to the suitability assumption of mainstream theory to explain how crime self-reinforces itself. Figure 3.3 recreates the micro-macro model again, adding link 6 to represent the feedback effect from crime to locational suitability. The feedback effect of crime must be filtered through the offender decision process.
before its consequences are felt again in the aggregate crime pattern. For this reason, this

Figure 3.3. Micro-macro causal structure incorporating positive feedback from crime to locational suitability.

The indirect nature of the crime-suitability feedback loop permits additional sources of “error” to obscure the effect. That is to say that crime must have a large enough effect on suitability conditions to be perceived by offenders (with little error) who might then increasingly view the area as suitable to search for targets. There is little research on offender interpretation of environmental cues, but one study has shown significant variation in location suitability effects on crime location choice (Townsley et al., 2016). This finding suggests either that (a) offenders have varying preferences in the types of places they select for crime or that (b) substantial error occurs when offenders interpret the same environmental cues. Townsley et al. (2016) suggest the former
explanation but the latter is equally plausible and begs the question “how large must suitability changes be to overcome interpretation errors and generate local changes in crime?” This interpretation implies that place-based interventions are likely to have mixed effects on average.

Crime suitability feedback is also a long-term process. Most place suitability characteristics that would be affected by crime (so as to increase it) change rather slowly. Hipp and Wickes (2017), for instance, could not find evidence that crime negatively affected collective efficacy over periods of two weeks, two years, or five years, but they do find that crime feeds back into concentrated disadvantage over 5-year intervals. As the authors note, “there is some evidence that higher levels of collective efficacy lead to lower levels of concentrated disadvantage, although this process may occur over a longer period” (Hipp & Wickes, 2017, p. 798). Other studies of the evolving relationship between crime and suitability characteristics are often conducted using longer time series involving decades (Bursik Jr & Webb, 1982; Cohen & Felson, 1979; Shaw & McKay, 1942), which could indicate the length of time it takes for these processes to unfold so that effects can be observed.

I contend that the positive feedback effects already proposed in geographic criminology are indirect, long-term, and subscribe to the suitability assumption of mainstream theory. For these reasons, the positive feedback effects already proposed in the literature differ considerably from the more direct feedbacks discussed herein that

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6 Suitability factors affected by crime that can change more quickly often have the effect of reducing crime, not increasing it. Hot spots policing, for example, responds to high crime places but has crime reduction effects Braga, A. A., Papachristos, A. V., & Hureau, D. M. (2014). The effects of hot spots policing on crime: An updated systematic review and meta-analysis. Justice Quarterly, 31(4), 633-663. The theoretical underpinning of hot spots policing expects “decreasing returns,” because more crime causes increases in social controls which will reduce the problem rather than reinforce it.
ignore the suitability assumption and are more likely to have immediate effects. These distinctions are important because they imply different approaches to crime reduction strategy, as I will discuss in Chapter 6.

**Nested feedback loops.** The discussion of macroscopic feedback leads to a combined theoretical model of path dependence as illustrated in Figure 3.4. An individual’s history of crime location choice positively influences re-selection. Individuals within a co-offending network or group influence one another’s crime location choices, albeit more indirectly (hence, shown as a dotted line). Positive feedbacks in the aggregate are filtered through locational suitability to indirectly influence crime location decisions. To reiterate an important point, individual and group-level feedbacks occur without respect to locational suitability and therefore are unaffected by changes made at locations.

**Figure 3.4.** Nested positive feedbacks in crime.
Path Dependent ‘Lock-in’

Positive feedbacks will cause crime problems to grow initially and become locked-in eventually. Lock-in means that a pattern becomes fixed and is resistant to changes thereafter. Lock-in follows directly from path dependence and Pólya urn theory (Arthur, 1994; Arthur et al., 1983, 1987; Chen & Kuba, 2013; Mahmoud, 2008). Positive feedbacks lock the system into an outcome, because events that occur later in the sequence have decreasing influence on the aggregate patterns.

Consider the following stylized example. Suppose a sample of offenders will commit 500 crimes, and in each event, they have the choice of committing the crime in one of $N$ possible areas denoted as $j_1, j_2, \ldots, j_N$. The probability that an offender selects each area is equal to $q_j$, the proportion (i.e., share) of all crimes that have occurred in area $j$ at the time the decision is made. Each area starts with one crime so that its share is equal to $q = 1/N$. Offenders take turns committing crimes one at a time by selecting an area proportional to $q_j$ at each location until all crimes are committed. The $q$ probabilities are updated after each event. This is a simple urn process and we can use it to explore the spatial patterns that emerge.

Figure 3.5 illustrates the urn process in the $N=5$ case over three realizations (independent runs of the process). The x-axis in each graph represents time, and the y-axis is the area’s “share” of the crimes ($q_j$). The lines show how each area’s share changes over time. In each realization of the process, the shares fluctuate rapidly at first but eventually settle into a stable pattern that changes very little. Initially, each event has a large influence on the relative crime frequencies, but events that occur later in the sequence become increasingly inconsequential. If we extended the graphs for longer
periods of time, the lines would appear even flatter. This is what lock-in looks like in a pure Pólya urn model where history and chance are all-powerful. Another thing to note is that each realization in Figure 3.X began with the same initial conditions where each area had one crime so that all areas had the same probability of taking the greatest share of crimes by the end. Yet, in each realization, a completely different pattern emerged. In the first, \( j_4 \) emerged with the greatest share of crimes, \( j_2 \) had the greatest share in the second, and \( j_5 \) had the greatest share in the third. Technically, any combination of shares that sum to 1.0 are possible and the outcome that emerges is completely unpredictable from the outset (Arthur, 1994; Arthur et al., 1983, 1987).

**Figure 3.5.** Three Realizations of a Pólya Urn Process with N=5 Options.
The above urn model illustrates path dependence and lock-in. The pattern becomes stable after a certain point. This results from positive feedback, and this is the type of process hypothesized in the proposed theoretical model. This is, of course, the extreme case where history and chance are all-powerful, but it demonstrates an important point about positive feedback processes. Once a pattern or path becomes locked-in, it is difficult to change course. If status quo bias is strong, it could mean that crime problems will become locked-in to certain areas. This is implied by theorists who suggest that feedback loops result in chronic crime problems and a “spiral of decay” (Skogan, 1992).

Lock-in by historical events seems to characterize crime patterns in some but not all contexts. Consider that the same high crime areas in Chicago appeared to have persisted from the time that early University of Chicago sociologists documented delinquency patterns in the early 1900s (Shaw & McKay, 1942; Thrasher, 2013) through the 1980s, before moving to the west and south areas of the city (Papachristos, 2013). Patterns of crime stability are observable in other cities over varying periods of time (Andresen et al., 2017; Andresen & Malleson, 2011; Braga et al., 2010; Vandeviver & Steenbeek, 2019; Weisburd et al., 2004). At the same time, other research suggests that crime patterns are much more dynamic and the same places are not always “hotspots” (Johnson & Bowers, 2008; Levin et al., 2017; Mohler et al., 2018). Instability is sometimes explained as an issue of spatial-temporal scale. To wit, smaller areas and shorter time periods tend to display greater instability simply because the window of observation is smaller (Hunt, 2016; Mohler et al., 2018). Nonetheless, an important question concerns the potential limits of pattern “lock-in” and how path dependence might explain instability. In other words, what mechanisms might facilitate “exit from
lock-in” when positive feedback mechanisms persist? I describe in the next section how the answer lies in the nested nature of positive feedback.

**Exit from Lock-in**

Lock-in occurs when positive feedback mechanisms cause patterns of behavior to repeat over time. But few patterns persist unchanged forever. Arthur (1988a) describes how an alternative class of mechanisms might explain re-contraction of a pattern that has formed. But I argue that a complete theoretical model should account for exit from a locked-in state without simply suggesting that the proposed mechanisms stop working and alternative processes take over. In the present context, I claim that exit from lock-in could result from three mechanisms: (1) offender death, desistance, and incapacitation; (2) crime network dynamics, and; (3) large exogenous shocks. Each is described in turn and have implications for crime reduction policy.

**Criminal career termination.** Multiple circumstances can result in the end of an offender’s criminal career. Whether they die, desist, or are otherwise incapacitated, all offenders will eventually stop committing crime. When this happens, their individual-level positive feedbacks are no longer relevant because they will not commit anymore crimes. Further, the individual’s crime history effects on others will begin to decay. The status quo options that they passed on to others may live on for some time but will eventually die if the torch is not passed on by other offenders. At the same time, the individual will no longer pass forward the feedback effects they “carried” from previous crimes, thereby killing an effect that was initiated before them. This all suggests that the
end of an offender’s criminal career has cascading effects. If the combined result is large enough, it could be sufficient to shake the system out of lock-in.

The above point ties path dependence theory to a variety of processes in the individual offending literature that might influence the number of individuals in the offending pool and their offending patterns. Relevant processes include the relationship between age and crime (i.e., age-crime curve), offending trajectories over the life course, societal level demographic changes, and other societal level changes that affect motivation to offend. Prior research claims that demographic changes do not explain large changes in crime over time. Levitt (1999) shows that the changing U.S. age structure following the baby boom, for example, cannot account for more than a one percent increase in aggregate crime rates. But demographic changes may not affect aggregate crime rates because of a lack of positive feedback in overall crime levels.

I contend that spatial crime patterns may be affected by these kinds of demographic processes because of positive feedbacks described herein. Status quo biases can cause groups of offenders to become locked-in to offending in a small number of places. But when these offenders are removed from the offending pool, it is possible that the feedback effects will not be passed along to other offenders. This could result in the high crime places exiting from lock-in. This type of process could explain why some places in cities are “hot spots” for a long period of time but eventually cool off as crime moves elsewhere. Further elaboration of this process is beyond the scope of this dissertation but could be an important step in exploring the limits of path dependent feedbacks.
**Crime network dynamics.** Relatedly, the size and stability of co-offending networks has major implications on how much positive feedback maintains pattern lock-in. Path dependence implies that large and stable co-offending networks create strong group-level positive feedbacks on aggregate patterns. But co-offending networks, including gangs, are known to be dynamic and unorganized (Charette & Papachristos, 2017; Klein, 1997; Klein & Maxson, 2010; Magliocca et al., 2019). Network change could explain why a crime pattern exits from lock-in if the positive feedback are disrupted. On the other hand, network change could also serve as a multiplying effect if status quo biases of one group are combined and overlap with those of another group. The point is that the structure of co-offending networks will undoubtedly have major consequences for crime pattern lock-in. Further examination of these processes are left to future work.

**Exogenous shocks.** Large scale events can have abrupt consequences on social systems (LaFree, 1999; Rosenfeld, 2018). It is likely that such events, such as widespread financial collapse or global public health crises, would be impactful enough to cause crime patterns to exit from lock-in. Such events are, by definition, unpredictable and unexpected (Black et al., 2012), and they can come from a large number of sources. While worth mentioning that exogenous shocks represent an important type of mechanism that can cause exit from lock-in, further elaboration is beyond the scope of this work and left to future inquiry.
Theoretical Limitations

The above arguments about path dependence exhibit many strengths. Empirical research supports the notion that present crime problems are often linked to the past, which could indicate positive feedback processes are at least partly responsible. Mechanisms that could underlie path dependence come from rich literatures in economics, political science, and other social science disciplines, as well as emerging research in criminology pertaining to offender decision making (Pogarsky et al., 2018), social networks (Faust & Tita, 2019; McGloin & Nguyen, 2013; Morselli, 2009; Papachristos & Bastomski, 2018; Tita & Boessen, 2011), and other unknown dependencies in crime (Loeffler & Flaxman, 2018; Mohler et al., 2011; Short et al., 2010; Short et al., 2008). Yet, there are important limitations to the path dependence argument that should not be overlooked.

**Theoretical inertia and mainstream resistance.** One inherent challenge with proposing path dependence within a given field of study. As mentioned in Chapter 1, path dependence theory is often at odds with conventional theory. In economics, Arthur (1990a) describes how neoclassical economics assumes diminishing returns (negative feedback) that result in predictable equilibriums in prices and market shares. These equilibriums represent optimal outcomes under the conditions. Path dependence proposes increasing returns (positive feedback) that “magnify small economic shifts” and produce multiple equilibrium points (Arthur, 1990a, p. 92). This deliberate contrast is difficult to justify and is often met with skepticism and criticism. Liebowitz and Margolis (1995) exemplify the kind of condemnation of path dependence theory, claiming that the
assumptions are implausible and lack empirical support. Critiques of path dependence have been presented in political literature as well (Kay, 2005).

The most pronounced criticism of path dependence is not denial of the positive feedback mechanisms themselves, but rather the rejection of conventional theory that creates so much controversy. A similar situation exists in the ecology literature. Hubbell (2001) proposed his unified neutral theory of biodiversity that outright rejects the role of species competition in determining the spatial patterning of organisms. Whereas traditional theory assumes that species competition and environmental heterogeneity determine where different species are found, the neutral theory essentially asks “what if there is no competition and environmental heterogeneity did not matter?” Some have argued that the neutral theory is incorrect and generates more scholarly heat than light (Abrams, 2001; McGill, 2003; Ricklefs, 2006), while others hold that the neutral theory is supported empirically (Rosindell et al., 2011) or at least serves as a useful counterfactual for comparing with conventional models (Alonso et al., 2006; Bell, 2005). The point is that path dependence and similar theoretical perspectives such as neutral theory have faced considerable criticism in their respective fields. This fact should not be omitted from the current work.

I assume path dependence operates alongside other theoretical processes. That is to say that both place and history matter. At some points in the manuscript, ideas are illustrated using extreme scenarios to develop intuition about how the processes work,

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7 Neutral theories have also been proposed in population genetics Kimura, M. (1983). *The neutral theory of molecular evolution*. Cambridge University Press.
not necessarily to mirror reality in every detail. Neither the “place matters” nor “history matters” perspectives should be viewed as wholly correct or incorrect, but rather as complimentary worldviews operating simultaneously. The key questions here are (1) what effect does history have on crime and (2) under what conditions can history override the effects of place in important ways?

**Alternative mechanisms.** Other mechanisms of positive feedback may also account for path dependence in crime. Coordination effects, like clustering effects in economics (e.g., agglomeration economies; Arthur, 1994), imply that criminal activity thrives off other types of crime. Violence, for instance, is well known to be related to the presence of criminal black markets where conventional means for solving disputes is unavailable (Anderson, 1999; Roth, 2012). Felson (2006) describes this process in ecological terms, stating that crimes can have ‘mutualistic’ relationships with other forms of criminal activity. Underground gun markets feed violence by providing offenders with weapons, and violence in turn increases the need for illicit weapons. Once the cycle of crime gets started, it self-reinforces itself through other crimes.

Another example of path dependence is the role of power dynamics. Retaliatory violence is one obvious example where victims seek to even an unsettled score against their attacker through the use of violence (Jacobs, 2004; Jacobs & Wright, 2006; Kubrin & Weitzer, 2003b; Mullins et al., 2004). Retaliating against an attacker who gets the upper hand restores the balance of power. These power dynamics often characterize gangland conflicts, as criminal groups compete for territory and dominance (Brantingham et al., 2012; Brantingham et al., 2019). These types of retaliatory cycles have been modeled in the same way that geographers study seismic activity; just as earthquakes
temporarily increase the likelihood of subsequent earthquakes in a predictable way, crime patterns can be modeled as a self-exciting point process (Mohler et al., 2011) or reaction-diffusion process (Short et al., 2010; Short et al., 2008) where one crime event increases the likelihood of future crime for a short time. Such examples demonstrate the potential for path dependence sequences to play a sizable role in certain contexts. This dissertation focuses only on status quo biases and co-offender imitation, but more work is needed to conceptualize and empirically assess alternative underlying mechanisms.

**Nonlinearity and chance.** Path dependence poses serious challenges to modeling and predicting social behavior. Positive feedbacks introduce indeterminacy which means that outcomes are unpredictable from the outset. A key feature of path dependence is that a very large number of equilibria (stable points) are possible, and nonlinearities make it difficult even to identify candidate states of the final pattern (Arthur, 1994). Modeling these systems requires powerful mathematical machinery that works better to explain the past than to predict the future. But a better understanding of how these types of systems work will likely provide clues as to how we might better cope with unpredictability or perhaps shed light on the possible effects that unpredictable change might have on the social world.

This implies that crime is subject to chance. Explanations of chance are rarely satisfying and most of science assumes nonrandom distributions (i.e., patterns) are evidence of nonrandom processes (Macy & Tsvetkova, 2015). This is reasonable, given that we can rarely manipulate chance processes and tend to just ignore them as “noise.” Therefore, one limitation of the path dependence argument is that some of the
explanation for crime involves unpredictable, chance events that could have substantial implications down the road.

**Conflation or mediation with locational suitability.** One potential counterpoint to the path dependence argument is that the underlying mechanisms that drive positive feedback are attributable, in part, to measurable heterogeneity in some condition. We can imagine that the mechanisms proposed to underlie path dependence, such as social network structure, are themselves a result of locational suitability processes. This would imply that path dependence as a class of mechanisms serves to mediate the effects of social-environmental variables rather than conflate them. More theoretical and empirical work is needed to address this possibility.

**Conclusion**

Path dependence is a general class of positive feedback processes that transcends social behaviors. Criminologists have considered positive feedbacks in crime, but they typically rely on crime suitability assumptions that filter the feedbacks. This chapter presents an alternative possibility that status quo biases in crime location choices of offenders generates positive feedback at microscopic levels of analysis. The implications for aggregate crime patterns include the concentration of crime events and stability of high crime, hotspot areas. As it relates to crime policy, history effects may override decreases in place suitability in some circumstances and render these strategies unsuccessful. Alternative approaches that address positive feedback mechanisms at the individual and network-levels are implied when history effects are strong. The next two chapters test these theoretical propositions. Chapter 4 provides empirical evidence for
status quo bias in crime location choice using a sample of crimes occurring in St. Louis, Missouri during 2017-18. Chapter 5 plays out the macroscopic consequences of these status quo biases to show the power of this path dependent process.
Chapter 4. Status Quo Bias in Crime Location Choice

The proposed theoretical model asserts that offenders tend to select the same locations for crime that they or their co-offenders previously selected. Re-selecting the status quo option (previous crime site) is considered a bias when more suitable locations are available. This chapter presents results testing for the status quo bias in offender decision making by examining whether previous crime sites influence crime site selection, net of suitability factors. The hypotheses for this analysis are the following:

1. Places where an offender has previously committed crimes are more likely than other places to be selected for crime, net of locational suitability factors.
2. Places where co-offenders have previously committed crimes are more likely than other places to be selected for crime, net of locational suitability factors.
3. The history effects above will be stronger when:
   a. The offender engages in more crimes overall (higher offending frequency).
   b. More crimes have been committed in the location.
   c. Previous crimes at the location were of the same crime type.
   d. Previous crimes at the location occurred more recently.

Data

The data used to test crime site selection hypotheses are for the city of St. Louis, Missouri. The population of St. Louis was estimated to equal roughly 320,000 residents during 2010, while the surrounding St. Louis County supports close to one million residents. St. Louis is a Midwestern, rust-belt city with a long history of racial
segregation, de-industrialization, and chronic disadvantage (Gordon, 2008). Crime, especially violent crime, is prominent in St. Louis. The homicide rate tends to be 10 times higher than in other comparable cities, with roughly 64 homicides per 100,000 annually during 2017-2018 as compared to the national average of about 5.6 homicides per 100,000. The homicide rate rose 62 percent between 2013 and 2015, consistent with a widespread homicide rise during the period (Lauritsen & Lentz, 2019; Rosenfeld & Fox, 2019), but the trend stabilized between 2015 and 2018.

**Figure 4.1.** Spatial distribution of 2017-2018 UCR Part I violent crime rate and Part I property crime rate per 100,000 population in city of St. Louis block groups (N=359).
Crime is heavily concentrated in certain areas of St. Louis as shown in Figure 4.1. Violent crime is predominately clustered on the north side of the city. Additional high violence areas exist along the eastern boundary of the city and in a high population area in the southeast (Dutchtown neighborhood). Property crime appears more dispersed than violent crime, with hot spots occurring primarily along the eastern boundary of the city, north, and southeast, and a few isolated areas in the southwest where affluence is higher. High crime areas are characterized by high disadvantage and a high percentage of black residents (Hipple et al., 2019; Lauritsen & Lentz, 2019).

**Crime incidents.** The crime incident data were provided by the St. Louis Metropolitan Police Department (SLMPD). The final sample consists of N=9,527 UCR Part I crimes occurring during 2017-2018. Data for all known crime incidents are stored by SLMPD in a relational database that consists of multiple datasets linked together by an incident ID. The databases used in the analysis include a main incident list with incident-level information (e.g., date, time, location), charges or crime types defining the incident, persons involved in the incident as an offender, victim, or witness, and personal information for each person involved (e.g., name, date of birth, address). Data were merged together using the incident ID key field as needed to construct the final dataset for analysis.

**Offender matching.** A central question in the choice analysis concerns the influence of past crimes on crime site selection. This requires using offending history for each offender (and their co-offenders) to construct variables to include in the models. The process to match offenders across incidents in the database involved creating a unique identifying number for each offender. Each time police enter individual information into
the record management system, the data entry person has the option to search for an
existing record of the individual and append the new information or add a new record.
Each individual is assigned a unique ID number by the system that links them across
incidents. It was discovered during data cleaning, however, that the same individuals
appear in the system under different ID numbers, suggesting that a new record was
created rather than appending new information to an old record.

A new unique identifying number was created that used personal information
stored in the system to override the system-assigned ID number to ensure that the same
individual was not stored in the system under multiple ID numbers. The primary
matching criterion is social security number; if two records contained the same social
security number, they are assigned the same unique ID. The second criterion was a
complete match of the individual’s first name, last name, and date of birth; for cases not
matched by social security number, records containing the exact same name and date of
birth were assigned a unique ID. After this process was completed, the remainder of the
records were assigned the system-provided ID number for matching.

Co-offender identification. A second central question in the analysis concerns
whether the site selection history of an individual’s co-offenders influenced their location
choices. The crime incident data were used to identify offenders who were involved in
the same incident to indicate co-offending. Previous research has used similar methods
and data to examine the role of social networks in crime. Papachristos (2009) examined
how social network structure explained gang homicide, and in particular, showed that
violence spreads through co-offending networks (see also: Charette & Papachristos,
2017; Papachristos et al., 2012; Papachristos et al., 2013). In a similar way, status quo
bias can spread through co-offending networks and influence where an individual will choose to commit a crime. I argue that even in the absence of detailed narratives describing each incident or arrest, a substantial amount of knowledge about who is associated with whom can be ascertained by observing co-involvement in the same crime incident.

Past research suggests that identifying who is actually observed to be involved with whom is better than inferring involvement via membership or affiliation with the same criminal group (Fleisher, 2005). In other words, even if self-nomination into a gang is a valid measure of membership (Decker et al., 2014), individuals who claim membership to the same gang or criminal group may never actually engage in any social interaction (Bouchard & Konarski, 2013; Fleisher, 2005). Conversely, individuals who engage in a large amount of social interaction may never claim affiliation to the same group (Morselli, 2009). It is best to rely on a more objective measurement of social interaction, such as being involved in the same crime incident or be arrested together at the same time and place (Brantingham et al., 2011).

Co-offender identification involved searching the offending history database to determine who had ever been involved in the same crime as an offender. Then, the offending histories of any co-offenders were merged with the respective offender in the sample to measure co-offending history at a given location. Similar to the offender history database, co-offender histories covered the time period from 2008-2018 and only crimes that occurred prior to the focal incident were considered in the location history.

The proposed analysis may reduce potential bias in the observed crime networks by including all crime records known to police for the extended period 2008-2018.
Observing 11 years’ worth of data increases the likelihood that any given offender’s general behavioral pattern will be observed, such that most places in which a repeat offender is known to have been involved in crime will be observed in the data. Including all types of crime, rather than focusing only on burglary for instance (Bernasco et al., 2015), may also increase the likelihood that co-offending will be observed. This is especially the case for serious crimes with higher clearance rates.

**Final sample.** The final sample includes N=9,527 crime location decisions committed by 7,162 offenders in 8,013 incidents. The sample represents 17.57 percent of the 45,607 UCR Part I crime incidents occurring during the study period. The vast majority of missing incidents were omitted due to missing offender data (either no offender listed or no known home address). Missingness varies by crime type, consistent with variation in clearance rates by type. Of their respective totals, 48 percent of homicides, 56 percent of rapes, 25 percent of robberies, 49 percent of aggravated assaults, 16 percent of burglaries, 11 percent of larcenies, and 14 percent of motor vehicle thefts are included in the sample.

Each incident in the sample involved 1.18 offenders on average (Median=1; SD=0.65; Min=1; Max=32). Incidents with multiple offenders are treated as multiple crimes, because each represents a location decision. Each offender was involved in 1.31 incidents in on average during 2017-2018 (Median=1; SD=1.12; Min=1; Max=37). Over the entire study period from 2008-2018, the average offender has a history of committing 2.51 incidents (Median=2; SD=2.63; Min=1; Max=39).

First-time offenders were involved in 4,130 of the crimes (43.4 percent). The remaining 5,396 crime location decisions (56.6 percent) involved an offender who had
previously committed crime and therefore had the possibility to re-select a previous crime site. Previous crime locations were re-selected 19.63 percent of the time. Similarly, offenders re-selected previous crime sites of their co-offenders 21.87 percent of the time.

Table 4.1 unpacks crime location re-selection rates in greater detail. Crime locations are more likely to be re-selected if they involve the same offense type than if the crime type is different. Offenders re-selected crime locations at a higher rate if the previous crime was committed at the location more recently (i.e., last 30 days) than if it were committed further in the past (i.e., greater than 6 months ago). Offender history and co-offender history re-selection rates are relatively comparable, suggesting that co-offenders may have considerable influence on offender decision making.

Table 4.1. Crime location re-selection by offenders in city of St. Louis, MO (2017-2018).

<table>
<thead>
<tr>
<th>Prior Offense Committed</th>
<th>By Offender</th>
<th>By Co-offender</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Count</td>
<td>% of Possible¹</td>
</tr>
<tr>
<td>In Same Location</td>
<td>1,059</td>
<td>19.63</td>
</tr>
<tr>
<td>…Same Type</td>
<td>722</td>
<td>22.75</td>
</tr>
<tr>
<td>…Different Type</td>
<td>443</td>
<td>10.72</td>
</tr>
<tr>
<td>…Within 30 Days</td>
<td>376</td>
<td>33.39</td>
</tr>
<tr>
<td>…31-180 Days</td>
<td>441</td>
<td>25.64</td>
</tr>
<tr>
<td>…&gt; 180 Days</td>
<td>555</td>
<td>11.55</td>
</tr>
</tbody>
</table>

NOTES:
¹ Number of times that a prior offense was committed divided by the possible number of crimes in which the offender could have re-selected a prior crime location.
² Total number of times that an offender re-selected a prior crime site divided by the total number of crimes committed by an offender who has crime history.
Figure 4.2 shows that the age distribution of the offenders follows the classic age-crime curve, with the average offender being 32.27 years old (Median=29.5; SD=12.10; Min=9; Max=81). More than 75 percent of the offenders are male, 83 percent are black, 15 percent are white, and less than 1 percent are Hispanic. Offenders committed crimes in locations that were 3.25 miles from their home address, on average (SD=3.37; Min=0.002; Max=29.45). One-fourth of offenders committed crimes within 0.53 miles from their home, and half of the offenses were committed within 2.22 miles of the offender’s home; the highly-skewed distribution is consistent with the journey to crime literature (Ackerman & Rossmo, 2015; Rengert, 2004; Rengert & Wasilchick, 1985).

(1) Age Crime Curve
(2) Journey to Crime Curve

Figure 4.2. Age of offenders and journey to crime distributions of 7,162 offenders involved in 9,527 UCR Part I crimes in city of St. Louis, MO (2017-2018).
**Discrete Choice Model**

The most appropriate analytic method to test the hypotheses is the discrete choice model. Offenders are presumed to engage in a multi-stage decision process when committing crime. The first stage is determining whether one is motivated and willing to commit crime, and the second stage involves choosing where to search for targets and commit the crime (Brantingham & Brantingham, 1981, 1984; Brantingham & Brantingham, 1993; Clarke & Cornish, 1985; Cornish & Clarke, 1986; Wikström et al., 2012). It is the second stage of selecting a location for crime that is the focus of the current analysis, and it involves selecting a discrete location to commit the crime among a set of alternative locations.

Discrete choice analysis has been applied extensively to study offender decision making in criminology (e.g., Bernasco, 2010a, 2010b; Bernasco & Block, 2009; Bernasco & Nieuwbeerta, 2004; Johnson & Summers, 2015; Lammers et al., 2015; Menting et al., 2016; Townsley et al., 2016). The discrete choice framework uses the multinomial logit model (i.e., conditional logit model) originally developed by McFadden (1973). This model of choice behavior adds a random component to a micro-economic utility function (random utility maximization) and is characterized by the following assumptions of the choice process (Ben-Akiva & Bierlaire, 1999; Ben-Akiva & Lerman, 1985). A decision-maker makes a choice by choosing among a mutually exclusive and exhaustive set of alternatives. Each alternative is characterized by a set of attributes that are evaluated by the decision-maker according to their attractiveness. The decision-maker then chooses the alternative that maximizes her utility. In most applications, preferences are revealed by the observed choice of the decision-maker (Bernasco, 2010a); in the
present context, the observed location of a crime is considered to be the alternative with
the highest preference attributes for a given offender.

In its most general form, the discrete choice framework can be stated formally in
the following way (Bernasco, 2010a). Suppose a decision maker \( n \) must choose among \( J \)
alternatives, each with a level of utility \( U_{ni} \) where \( i \) denotes each alternative. If the
decision maker expects greater utility from alternative \( i \) than all of \( J \) alternatives, then the
principle of utility maximization asserts that alternative \( i \) will be selected. Actual utilities
are unobserved by the researcher but are of course known by the decision maker. What is
observed are the \( J \) alternatives, some of their attributes \( a_{ni} \), and some attributes of the
decision maker \( d_n \). A representative utility function \( V \) can then be specified that links
these observed attributes to the expected utility for a given decision maker:

\[
V_{ni} = V(a_{ni}, d_n) \forall i. \tag{4.1}
\]

Because the actual utility function \( U \) is not completely observed, a random error term is
added to the observed utility function \( V \) such that:

\[
U_{ni} = V_{ni} + \varepsilon_{ni}. \tag{4.2}
\]

The probability that \( i \) is chosen over alternatives by decision-maker \( n \) is then:

\[
P_{ni} = \Pr (U_{ni} > U_{nj}) \forall j \neq i \tag{4.3}
\]

\[
P_{ni} = \Pr (V_{ni} + \varepsilon_{ni}) > (V_{nj} + \varepsilon_{nj}) \forall j \neq i
\]

The multinomial logit model can then be derived if we can assume that the
unobserved random utility components are independent and identically distributed
according to an extreme value distribution (McFadden, 1973). The probability that
decision-maker \( n \) chooses alternative \( i \) is defined as:
\[ P_{ni} = \frac{e^{V_{ni}}}{\sum_{j=1}^{J} e^{V_{nj}}} \]  

(4.4)

The utility function \( V \) can be parameterized as a linear function given by:

\[ P_{ni} = \frac{e^{\beta' X_{ni}}}{\sum_{j=1}^{J} e^{\beta' X_{nj}}} \]  

(4.5)

where \( X \) is a vector of observed attributes that vary across alternatives and \( \beta' \) is a vector of parameters that can be estimated. The multinomial logit model can be extended to address potential criticisms of the basic formulation, such as the independence of irrelevant alternatives property (Ben-Akiva & Lerman, 1985; Bernasco, 2010a). Interested readers are referred to Train (2009) for elaborations of these extensions.

The multinomial logit model offers a convenient option for investigating the role of different influences driving crime site selection. Here, crime sites refer to the block group where the crime was committed, such that \( J \) equals the total number of block groups in the city and each block group is denoted by the subscript \( i \). We can rewrite the representative utility function represented by equation (4.1) as:

\[ V_{ni} = V(s_{ni}, h_{ni}) \forall i \]  

(4.6)

where \( s_{ni} \) represents location suitability and \( h_{ni} \) represents history effects via path dependence, such that the utility of selecting alternative \( i \) for potential offender \( n \) is:

\[ U_{ni} = V(s_{ni}, h_{ni}) + \varepsilon_{ni}. \]  

(4.7)

Note here that I choose not to model offender attributes as represented in equation (4.1) as \( d_n \), but they could be incorporated. The corresponding probability that alternative \( i \) is selected from alternatives can then be written as a linear function of suitability and history effects as:
\[ P_{ni} = \frac{e^{\delta s_{ni} + \gamma h_{ni}}}{\sum_{j=1}^{J} e^{\delta s_{nj} + \gamma h_{nj}}} \]  

(4.8)

where \( \delta \) and \( s \) represent vectors of suitability parameters and observed variables respectively and \( \gamma \) and \( h \) represent vectors of parameters and observed variables respectively for history effects.

The data structure for modeling discrete choices is different than other modeling techniques. Each crime incident is represented by \( J \) records, where \( J \) represents the number of potential places available to commit the crime. Columns in the dataset represent characteristics of each alternative \( i \) that are unique to the individual \( n \) who made the choice. The dependent variable is a categorical value that is coded as ‘1’ if the crime was committed in that block group and ‘0’ otherwise. Each crime in the dataset will therefore have \( J - 1 \) records coded as ‘0’ for the dependent variable and one record coded as ‘1’.

**Spatial choice unit.** Offenders in this analysis are assumed to select a block group to commit crime from all 359 block groups in the city of St. Louis.\(^8\) Research has used a variety of spatial units to test offender location choice, from street segments (Bernasco, 2010a) to zip code areas (Lammers et al., 2015) and census tracts (Bernasco & Block, 2009). Neighborhood and community-level research has a long history in criminology because larger areas are believed to have central importance in social organization (Hunter, 1979; Keller, 1968; Taylor, 2015). Recently, many crime and place criminologists argue that street segments are a superior unit of analysis because these micro areas minimize within-unit heterogeneity (St. Jean, 2008; Steenbeek & Weisburd,

---

\(^8\) One block group with zero population located in Forest Park is omitted from analysis.
2016; Weisburd, 2015). Others argue, however, that consideration of larger areas is still of theoretical importance (Boessen & Hipp, 2015).

In the context of offender choice, the ecological characteristics of areas larger than streets are important in determining where an offender decides to search for targets (St. Jean, 2008; Wright & Decker, 1996, 1997). In St. Louis in particular, neighborhood boundaries are important psychological markers between different types of places and have long historical significance (Gordon, 2008; Wayman, 1980). This is demonstrated by active robbers interviewed in St. Louis who mentioned particular neighborhoods by name to indicate the “best areas” for crime (Wright & Decker, 1997, p. 74).

The block group contains smaller amounts of within-unit heterogeneity than census tracts but is also large enough to reduce computational difficulty. Consider that the data structure for discrete choice creates a dataset with the number of rows equal to the number of alternate areas \( J \) multiplied by the number of crimes. This means that there are 359 rows for each crime \( N=9,527 \) for a total of 3,420,193 records. If a smaller unit of analysis were used such as street segments, the dataset would contain more than 150 million records and the discrete choice models would be difficult to converge. Bernasco (2010a) shows how a random sample of alternative places can be used to proxy all choices in the decision, but it does not seem intuitive that offenders consider thousands of alternative options when making their selection. Further, economic data are not available from the American Community Survey for areas smaller than block groups, and this variable is an important social indicator for locational suitability. The block group serves as a balance between micro places and larger neighborhood or community areas.
**History variables.** Variables are created to measure offender and co-offender history at each of the $J$ alternative places. For the majority of the analyses, places where an offender had previously committed a crime are coded as ‘1’ and ‘0’ otherwise. Places where someone in an offender’s co-offending network had previously committed a crime are coded as ‘1’ and ‘0’ otherwise. The model to test Hypothesis 3B uses continuous history variables, where the value at each alternative location represents the number of times a previous crime had been committed there.

**Locational suitability variables.** The individual choice hypotheses listed above specify that status quo biases operate independent from place suitability considerations. A large set of control variables are included in the analysis to represent various aspects of locational suitability. Table 4.2 summarizes block group suitability characteristics in St. Louis. Data for these variables come from the American Community Survey (2013-2017), city of St. Louis land use (2016) and 311 call databases (2015-2016), and the police department (2015-2016). All measures were created independently and merged with the crime location choice dataset for analysis.

Variables from the American Community Survey include total population, percent of males aged 15-24, racial composition, and socioeconomic indicators. Racial composition measures were used to create a racial heterogeneity variable measured as a Hirschman-Herfindahl index, which is the sum of the squared proportions of each racial group (i.e., white, black, Asian, Native American, Hawaiian-Pacific islander, other race, two or more races). Disadvantage is a composite index created using several indicators and principal components analysis to combine percent black population, percent female-
headed households with children, percent below poverty line, percent receiving public assistance, and percent unemployed ($\alpha=0.683$).

Table 4.2. Descriptive statistics for location suitability characteristics in city of St. Louis block groups (N=359).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Community Structure (2013-17)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Population</td>
<td>877.07</td>
<td>385.15</td>
<td>128.00</td>
<td>2,389.00</td>
</tr>
<tr>
<td>% Young Males Age 15-24</td>
<td>6.19</td>
<td>5.51</td>
<td>0.00</td>
<td>35.14</td>
</tr>
<tr>
<td>Racial Heterogeneity Index</td>
<td>2.83</td>
<td>2.13</td>
<td>0.00</td>
<td>6.96</td>
</tr>
<tr>
<td>Disadvantage Index</td>
<td>0.00</td>
<td>1.00</td>
<td>-1.60</td>
<td>2.86</td>
</tr>
<tr>
<td>% Black Population</td>
<td>50.58</td>
<td>37.63</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>% Female-headed H-holds</td>
<td>20.05</td>
<td>19.16</td>
<td>0.00</td>
<td>89.29</td>
</tr>
<tr>
<td>% Below Poverty Line</td>
<td>25.88</td>
<td>17.74</td>
<td>0.00</td>
<td>83.68</td>
</tr>
<tr>
<td>% With Public Assist.</td>
<td>2.93</td>
<td>3.85</td>
<td>0.00</td>
<td>21.74</td>
</tr>
<tr>
<td>% Unemployed</td>
<td>11.14</td>
<td>10.89</td>
<td>0.00</td>
<td>56.44</td>
</tr>
<tr>
<td><strong>Land Use/Risky Facilities (2016)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Land Use Diversity Index</td>
<td>3.21</td>
<td>2.13</td>
<td>0.07</td>
<td>7.90</td>
</tr>
<tr>
<td># of Secondary Schools</td>
<td>0.04</td>
<td>0.24</td>
<td>0.00</td>
<td>3.00</td>
</tr>
<tr>
<td># of Bars</td>
<td>0.80</td>
<td>1.33</td>
<td>0.00</td>
<td>12.00</td>
</tr>
<tr>
<td><strong>Social Control (2015-16)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>311 Call Rate per 1,000 $^1$</td>
<td>27.20</td>
<td>23.17</td>
<td>0.80</td>
<td>185.54</td>
</tr>
<tr>
<td>Arrest Rate per 1,000</td>
<td>200.68</td>
<td>312.78</td>
<td>5.16</td>
<td>2798.45</td>
</tr>
<tr>
<td>Police Activity per 1,000</td>
<td>530.40</td>
<td>502.71</td>
<td>27.58</td>
<td>3025.06</td>
</tr>
<tr>
<td>**Crime Rate per 100,000 (2017-18)$^2$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial lag</td>
<td>7,968.60</td>
<td>6,336.38</td>
<td>644.70</td>
<td>47,200.77</td>
</tr>
<tr>
<td></td>
<td>7,099.20</td>
<td>3,870.54</td>
<td>1,189.70</td>
<td>22,936.38</td>
</tr>
</tbody>
</table>

**NOTES:**
1. Average annual rate 2014-16.
2. Used to measure unobserved heterogeneity in crime suitability.
Tax assessment data for all parcels in the city of St. Louis were used to measure land use and risky facilities within block groups. A Hirschman-Herfindahl index was created to measure land use diversity (e.g., commercial, residential, transportation, service, parks, industrial, entertainment, vacant). The number of schools and the number of bars is also included to represent two risky facilities examined in the literature (Bowers, 2014; Eck et al., 2007; Ratcliffe, 2012; Roncek & LoBosco, 1983; Roncek & Maier, 1991).

Common sources of social control studied in the literature include residents themselves who act informally to reduce crime (Browning et al., 2004; Sampson et al., 1997) as well as formal police presence (Braga et al., 2014; Braga & Weisburd, 2010). The 311 call rate is used as a proxy for informal social control (O'Brien, 2016; Wheeler, 2018) and measures the number of citizen calls to 311 for issues related to crime and disorder per 1000 residents. The number of arrests and police activities per 1000 population are used as measures of formal social control. Arrests may indicate to offenders the certainty apprehension for committing crimes in the area, which is arguably an effective form of deterrence (Nagin, 2013). Police activities serve as a proxy for police presence and include direct patrols, foot patrols, proactive checks (vehicle, pedestrian, building), investigations, problem-oriented policing activities, and pursuits.

**Unmeasured locational suitability.** One challenge to measuring locational suitability is identifying all potential place characteristics that contribute to this ecological concept and correctly specifying their complex relationships with crime. For present purposes, I seek only to control for locational suitability and do not need to identify which social-environmental factors vie for influence. One way to control for all
suitability characteristics related to crime is to include an aggregate measure of the aggregate crime rate as an independent variable in the model.

If we can assume that the crime distribution represents optimal conditions as perceived on average across all offenders, then all suitability characteristics are absorbed in the aggregate measure of crime itself. If this assumption is tenable, then we might say that residual variation in crime that is unexplained by locational suitability could potentially be explained by the status quo bias. Conversely, attenuation of the locational suitability control variable when adding path dependent effects suggests conflation between the two processes that cannot be separated. A contemporaneous measure of the aggregate crime rate can therefore serve as a proxy for current locational suitability, absorbing influence of all related social-environmental factors. A spatially lagged version of this variable derived from a first-order adjacency spatial weights matrix (described in detail below) will also be included to control for suitability influence in neighboring areas. Spatial spillover from conditions in nearby areas is well-known in the literature (Anselin, 1988; Mears & Bhati, 2006; Messner et al., 1999). It is possible that these controls for locational suitability will also absorb some influence from unmeasured history effects, making the analysis a more conservative test of path dependence through the proposed mechanisms.

**Spatial proximity to offender home.** Another control variable used in analysis is the spatial proximity of the block group to the offender’s home block group. The journey to crime literature suggests that offenders tend to commit their crimes closer to their homes, but not necessarily in the immediate vicinity (Rengert, 2004; Rossmo, 1999). This is consistent with crime pattern theory because individuals are more familiar with areas
close to their home (Brantingham & Brantingham, 1981; Brantingham & Brantingham, 1993). Spatial proximity is measured as one divided by the Euclidean distance between the point location of the offender’s home and the centroid of the given block group.

**Results**

The discrete choice analysis begins by modeling the history effects of previously selecting a block group on the decision to commit a crime. Results from the conditional logit model are presented in Table 4.3. Model 1 shows that the odds an offender selected a previous location from their offending history are 13.27 times higher than selecting a location where they did not previously offend (SE=1.37; p<.001), controlling for spatial proximity to the offender’s home block group. The odds of selecting a previous crime site of a co-offender are 3.47 times higher than a location where a co-offender has not committed a crime (SE=0.43; p<.001). Model 2 includes locational suitability factors without considering offender or co-offender crime history. Consistent with previous research and mainstream theory, offenders are more likely to select places with higher population and disadvantage that are racially diverse. Locations with a high rate of police activity are also more likely to be selected, indicative of the bi-directional relationship between crime and police efforts (Simpson & Hipp, 2019). The aggregate crime rate absorbs the effects of many other suitability factors (e.g., number of bars, 311 call rate, arrest rate) found in other studies (Bernasco & Block, 2009; Lammers et al., 2015).
Table 4.3. Results from conditional logit models examining history and location suitability effects on 9,527 UCR Part I crime location choices by 7,162 offenders in the city of St. Louis (2017-2018).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1 History Effects</th>
<th>Model 2 Place Effects</th>
<th>Model 3 Combined</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OR</td>
<td>SE</td>
<td>OR</td>
</tr>
<tr>
<td>History Effects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Offender Previously Chose</td>
<td>13.269*</td>
<td>1.375</td>
<td>10.315*</td>
</tr>
<tr>
<td>Co-offender Previously Chose</td>
<td>3.466*</td>
<td>0.426</td>
<td>3.096*</td>
</tr>
<tr>
<td>Spatial Proximity to Suspect Home</td>
<td>1.260*</td>
<td>0.017</td>
<td>1.303*</td>
</tr>
<tr>
<td>Community Structure</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Residential Population</td>
<td>1.001*</td>
<td>0.000</td>
<td>1.001*</td>
</tr>
<tr>
<td>% Young Males (15-24)</td>
<td>0.992*</td>
<td>0.002</td>
<td>0.992*</td>
</tr>
<tr>
<td>Racial Heterogeneity Index</td>
<td>1.032*</td>
<td>0.008</td>
<td>1.027*</td>
</tr>
<tr>
<td>Disadvantage Index</td>
<td>1.227*</td>
<td>0.019</td>
<td>1.204*</td>
</tr>
<tr>
<td>Land Use and Risky Facilities</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Land Use Diversity Index</td>
<td>1.006</td>
<td>0.008</td>
<td>1.014</td>
</tr>
<tr>
<td># of Secondary Schools</td>
<td>1.044</td>
<td>0.054</td>
<td>1.049</td>
</tr>
<tr>
<td># of Bars</td>
<td>0.999</td>
<td>0.008</td>
<td>0.996</td>
</tr>
<tr>
<td>Social Control</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>311 Call Rate (x100)</td>
<td>1.062</td>
<td>0.045</td>
<td>1.008</td>
</tr>
<tr>
<td>Arrest Rate (x100)</td>
<td>0.999</td>
<td>0.004</td>
<td>0.999</td>
</tr>
<tr>
<td>Police Activity (x100)</td>
<td>1.027*</td>
<td>0.003</td>
<td>1.023*</td>
</tr>
<tr>
<td>Unobserved Heterogeneity</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crime Rate (x100)</td>
<td>1.005*</td>
<td>&lt;0.001</td>
<td>1.005*</td>
</tr>
<tr>
<td>Spatial Lag (x100)</td>
<td>1.000</td>
<td>&lt;0.001</td>
<td>1.000</td>
</tr>
<tr>
<td>Pseudo R-square</td>
<td>0.087</td>
<td>0.087</td>
<td>0.120</td>
</tr>
</tbody>
</table>

NOTES:
- OR=odds ratio; SE=standard errors clustered within offenders.
- *p < .05 (two-tailed).

Model 3 in Table 4.3 is a combined model showing the independent influences of offending histories and locational suitability. The pseudo r-squared for the combined model is higher than in the other models indicating superior model fit. The offender and co-offender history effects remain positive and significant. Given that measured and unmeasured locational suitability is controlled in this third model, these coefficients are
interpreted as the effects of status quo bias. The social-environmental factors and the aggregate crime rate (unmeasured suitability) should completely absorb the effects of offending history if offenders select crime sites solely on the basis of locational suitability. But Model 3 indicates that the odds an offender chooses one of their prior crime sites are more than 10 times higher than the odds of selecting an alternative location (SE=0.96; p<.001), and the odds of selecting a co-offender’s previous crime site are more than 3.09 times the odds of selecting an alternative location (SE=0.34; p<.001). These results confirm Hypothesis 1 and Hypothesis 2 that previous crime locations have higher odds of being selected for crime than other locations, net of locational suitability.

Additional models were estimated to examine the third set of hypotheses considering frequency, timing, and type of offending history and assess robustness of the history effects. First, Table 4.4. considers whether history effects are stronger for low-level of high-level offenders. Offenders are split into four categories: first-time offenders, second-time offenders, offenders with 2-5 previous crimes, and offenders with more than 5 previous crimes. The results show that individuals are affected by status quo bias, regardless of their observed offending frequency. The odds a high-rate offender (>6 previous crimes) re-selects a location for crime are almost 12 times higher than the odds of selecting a new crime site (OR=11.801; SE=1.525; p<.001), and the odds are 15.729 (SE=2.999; p<.001) and 9.212 times (SE=1.449; p<.001) higher for 2\textsuperscript{nd} time offenders and offenders with 2-5 previous offenses, respectively. Similarly, all groups are influenced by the crime location history of their co-offenders. This is especially true for first-time offenders, who had odds of re-selecting a co-offender’s prior crime site that

---

\(^9\) Note that first-time offenders cannot be influenced by their own history but can be affected by co-offender history. Hence, the first-time offender model does not include an offender history effect.
were nearly 10 times higher than the odds of selecting a new crime site (SE=3.140; p<.001). This co-offender history effect on first-time offenders is much higher than that for other offenders, for whom the odds ratio is closer to 3.0 for each offending group. Regarding Hypothesis 3A, the results do not suggest that offending history at a location is more important for higher rate offenders.

Next, the history effects were broken down further to test hypotheses about the frequency of previous crimes at the location (H3B), similar or different previous crimes at the location (H3C), and timing since previous crime (H3D). The first model in Table 4.5 shows the results using a continuous measure of prior crime location selection. The offender history effect remains significant and positive (OR=3.364; SE=0.334; p<.001), but the co-offender effect no longer significant at the .05 level (OR=0.980; SE=0.034; p=.156). Model 2 in Table 4.5 shows that the both offender and co-offender history effects are stronger when the previous crime at the location was of the same type than when it was a different offense type. These results largely support Hypothesis 3B and 3C, with the exception that a greater number of crimes committed by co-offenders at the location do not affect the likelihood of choosing the location.

Regarding Hypothesis 3D, there is unexpected temporal variation in the history effects that is not the same for offender and co-offender history. An offender’s own history of crime at the location always has a significant and positive effect on the likelihood of re-selecting the site, but the strongest effect is observed when the previous crime was committed between 31 and 180 days prior to the crime (OR=16.676; SE=3.096; p<.001). Hypothesis 3D expected a simple time decay in the effect of prior crime location selection, consistent with the idea that memory decays over time. Instead,
the effect is stronger after 30 days have passed, perhaps suggesting that offenders are afraid to return immediately to the same location until it cools down.

By contrast, offenders are extremely likely to re-select locations of co-offenders for crimes committed in the recent 30 days (OR=1.26.24; SE=41.167; p<.001). The history effect is then significant and negative for co-offender crimes committed between 31 and 180 days prior (OR=0.089; SE=0.032; p<.001) and is positive and significant for those occurring more than 180 days prior to the focal crime (OR=1.845; SE=0.026; p<.001). These effects suggest that offenders may be trying to quickly capitalize on opportunities to commit crime that they hear about through their co-offenders and do not perceive the same increases in risk associated with prior crimes occurring there.

A final set of discrete choice models were estimated to test whether the offending history effects differ by crime type. The results are shown in Table 4.6 for violent offense types and Table 4.7 for property offense types. The main effects from offender and co-offender history are positive and significant as expected for all crime types, with the exception of a nonsignificant co-offender history effect in rape location decisions. Homicides and robberies have higher co-offender history effects than offender history effects, which is the opposite for all other crime types. This may suggest that offenders rely more heavily on where their co-offenders have committed these crimes before than their own history. The co-offender effect is nearly as large as the offender history effect for motor vehicle theft as well, perhaps because these crimes are often committed in groups. Despite these differences in history effects by offense type, the general conclusion that “history matters,” net of locational suitability, suggests the important role of status quo bias in crime location selection.
Table 4.4. Results from conditional logit models examining history and location suitability effects on UCR Part I crime location choices in the city of St. Louis (2017-2018), by individual offending frequency.

<table>
<thead>
<tr>
<th>Variable</th>
<th>1st Time Offender</th>
<th>2nd Time Offender</th>
<th>2-5 Previous Crimes</th>
<th>&gt; 5 Previous Crimes</th>
</tr>
</thead>
<tbody>
<tr>
<td>DV: Block Group Chosen for Crime</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>History Effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Offender Previously Chose</td>
<td>-</td>
<td>15.729*</td>
<td>9.212*</td>
<td>11.801*</td>
</tr>
<tr>
<td>Co-offender Previously Chose</td>
<td>9.681*</td>
<td>2.697*</td>
<td>2.968*</td>
<td>3.036*</td>
</tr>
<tr>
<td>Spatial Proximity to Offender Home</td>
<td>1.419*</td>
<td>1.220*</td>
<td>1.193*</td>
<td>1.184*</td>
</tr>
<tr>
<td>Community Structure</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Residential Population</td>
<td>1.001*</td>
<td>1.001*</td>
<td>1.001*</td>
<td>1.001*</td>
</tr>
<tr>
<td>% Young Males (age 15-24)</td>
<td>0.991*</td>
<td>0.995</td>
<td>0.998</td>
<td>0.983*</td>
</tr>
<tr>
<td>Racial Heterogeneity Index</td>
<td>1.005</td>
<td>1.029*</td>
<td>1.014</td>
<td>1.066*</td>
</tr>
<tr>
<td>Disadvantage Index</td>
<td>1.128*</td>
<td>1.256*</td>
<td>1.318*</td>
<td>1.183*</td>
</tr>
<tr>
<td>Land Use and Risky Facilities</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Land Use Diversity Index</td>
<td>1.051*</td>
<td>1.032</td>
<td>0.989</td>
<td>0.965</td>
</tr>
<tr>
<td># of Secondary Schools</td>
<td>1.090</td>
<td>1.102</td>
<td>0.991</td>
<td>0.922</td>
</tr>
<tr>
<td># of Bars</td>
<td>1.013</td>
<td>1.001</td>
<td>0.992</td>
<td>0.973</td>
</tr>
<tr>
<td>Social Controls</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>311 Call Rate (x100)</td>
<td>0.979</td>
<td>1.095</td>
<td>0.944</td>
<td>1.047</td>
</tr>
<tr>
<td>Arrest Rate (x100)</td>
<td>0.999</td>
<td>1.000</td>
<td>1.003</td>
<td>0.992</td>
</tr>
<tr>
<td>Police Activity (x100)</td>
<td>1.030*</td>
<td>1.012</td>
<td>1.013</td>
<td>1.022*</td>
</tr>
<tr>
<td>Unobserved Suitability</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crime Rate (x100)</td>
<td>1.004*</td>
<td>1.005*</td>
<td>1.006*</td>
<td>1.006*</td>
</tr>
<tr>
<td>Spatial Lag (x100)</td>
<td>1.000</td>
<td>1.001</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Model Statistics</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pseudo R-square</td>
<td>0.110</td>
<td>0.107</td>
<td>0.111</td>
<td>0.181</td>
</tr>
<tr>
<td>N (# Crime Location Choices)</td>
<td>3,647</td>
<td>1,754</td>
<td>1,926</td>
<td>2,200</td>
</tr>
<tr>
<td># of Offenders</td>
<td>3,647</td>
<td>1,401</td>
<td>1,423</td>
<td>691</td>
</tr>
</tbody>
</table>

NOTES: * p < .05 (two-tailed).
OR=odds ratio; standard errors clustered within offenders (not shown).
Table 4.5. Results from conditional logit models examining history and location suitability effects on UCR Part I crime location choices in the city of St. Louis (2017-2018), by history effect type.

DV: Block Group Chosen for Crime

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1 OR</th>
<th>Model 2 OR</th>
<th>Model 3 OR</th>
</tr>
</thead>
<tbody>
<tr>
<td>History Effects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Offender Previous Frequency</td>
<td>3.364*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Offender Previously Chose…</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Same Crime Type</td>
<td>10.135*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Different Crime Type</td>
<td>5.842*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>In Previous 30 Days</td>
<td></td>
<td>2.167*</td>
<td></td>
</tr>
<tr>
<td>In Previous 31-180 Days</td>
<td></td>
<td>16.676*</td>
<td></td>
</tr>
<tr>
<td>More than 180 Days Ago</td>
<td></td>
<td>5.715*</td>
<td></td>
</tr>
<tr>
<td>Co-offender Previous Frequency</td>
<td>0.980</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Co-offender Previously Chose…</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Same Crime Type</td>
<td>6.671*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Different Crime Type</td>
<td>1.061</td>
<td></td>
<td></td>
</tr>
<tr>
<td>In Previous 30 Days</td>
<td></td>
<td>126.237*</td>
<td></td>
</tr>
<tr>
<td>In Previous 31-180 Days</td>
<td></td>
<td>0.089*</td>
<td></td>
</tr>
<tr>
<td>More than 180 Days Ago</td>
<td></td>
<td>1.845*</td>
<td></td>
</tr>
<tr>
<td>Spatial Proximity to Suspect Home</td>
<td>1.279*</td>
<td>1.270*</td>
<td>1.271*</td>
</tr>
<tr>
<td>Community Structure</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Residential Population</td>
<td>1.001*</td>
<td>1.001*</td>
<td>1.001*</td>
</tr>
<tr>
<td>% Young Males (age 15-24)</td>
<td>0.992*</td>
<td>0.992*</td>
<td>0.991*</td>
</tr>
<tr>
<td>Racial Heterogeneity Index</td>
<td>1.026*</td>
<td>1.025*</td>
<td>1.026*</td>
</tr>
<tr>
<td>Disadvantage Index</td>
<td>1.214*</td>
<td>1.212*</td>
<td>1.213*</td>
</tr>
<tr>
<td>Land Use and Risky Facilities</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Land Use Diversity Index</td>
<td>1.013</td>
<td>1.014</td>
<td>1.017*</td>
</tr>
<tr>
<td># of Secondary Schools</td>
<td>1.048</td>
<td>1.030</td>
<td>1.036</td>
</tr>
<tr>
<td># of Bars</td>
<td>0.997</td>
<td>0.997</td>
<td>0.997</td>
</tr>
<tr>
<td>Social Controls</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>311 Call Rate (x100)</td>
<td>1.059</td>
<td>1.029</td>
<td>1.037</td>
</tr>
<tr>
<td>Arrest Rate (x100)</td>
<td>0.998</td>
<td>0.999</td>
<td>1.000</td>
</tr>
<tr>
<td>Police Activity (x100)</td>
<td>1.024*</td>
<td>1.024*</td>
<td>1.024*</td>
</tr>
<tr>
<td>Unobserved Suitability</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crime Rate (x100)</td>
<td>1.005*</td>
<td>1.005*</td>
<td>1.005*</td>
</tr>
<tr>
<td>Spatial Lag (x100)</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Pseudo R-square</td>
<td>0.106</td>
<td>0.124</td>
<td>0.130</td>
</tr>
</tbody>
</table>

NOTES:
OR=odds ratio; standard errors clustered within offenders (not shown).
* p < .05 (two-tailed).
Table 4.6. Results from conditional logit models examining history and location suitability effects on UCR Part I violent crime location choices in the city of St. Louis (2017-2018), by offense type.

<table>
<thead>
<tr>
<th>DV: Block Group Chosen for Crime</th>
<th>Homicide OR</th>
<th>Rape OR</th>
<th>Robbery OR</th>
<th>Agg. Assault OR</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Variable</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>History Effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Offender Previously Chose</td>
<td>3.168*</td>
<td>4.907*</td>
<td>3.201*</td>
<td>6.691*</td>
</tr>
<tr>
<td>Co-offender Previously Chose</td>
<td>10.337*</td>
<td>1.135</td>
<td>9.721*</td>
<td>3.170*</td>
</tr>
<tr>
<td>Spatial Proximity to Suspect Home</td>
<td>1.399*</td>
<td>1.725*</td>
<td>1.167*</td>
<td>1.421</td>
</tr>
<tr>
<td>Community Structure</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Residential Population</td>
<td>1.001*</td>
<td>1.001*</td>
<td>1.001*</td>
<td>1.001*</td>
</tr>
<tr>
<td>% Young Males (age 15-24)</td>
<td>0.997</td>
<td>1.001</td>
<td>1.005</td>
<td>0.997</td>
</tr>
<tr>
<td>Racial Heterogeneity Index</td>
<td>1.103*</td>
<td>1.035</td>
<td>1.112*</td>
<td>1.061*</td>
</tr>
<tr>
<td>Disadvantage Index</td>
<td>1.266</td>
<td>0.948</td>
<td>1.150*</td>
<td>1.206*</td>
</tr>
<tr>
<td>Land Use and Risky Facilities</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Land Use Diversity Index</td>
<td>1.042</td>
<td>1.077*</td>
<td>1.043*</td>
<td>1.026*</td>
</tr>
<tr>
<td># of Secondary Schools</td>
<td>0.148</td>
<td>1.092</td>
<td>1.264*</td>
<td>1.010</td>
</tr>
<tr>
<td># of Bars</td>
<td>0.882*</td>
<td>1.040</td>
<td>1.089*</td>
<td>1.011</td>
</tr>
<tr>
<td>Social Controls</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>311 Call Rate (x100)</td>
<td>0.484</td>
<td>0.985</td>
<td>0.750</td>
<td>1.069</td>
</tr>
<tr>
<td>Arrest Rate (x100)</td>
<td>1.030</td>
<td>0.961</td>
<td>0.955*</td>
<td>1.010</td>
</tr>
<tr>
<td>Police Activity (x100)</td>
<td>0.995</td>
<td>0.971</td>
<td>1.020*</td>
<td>0.994</td>
</tr>
<tr>
<td>Unobserved Suitability</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crime Rate (x100)¹</td>
<td>1.420*</td>
<td>1.616*</td>
<td>1.067*</td>
<td>1.044*</td>
</tr>
<tr>
<td>Spatial Lag (x100)</td>
<td>1.074</td>
<td>1.284*</td>
<td>1.028*</td>
<td>1.024*</td>
</tr>
<tr>
<td>Model Statistics</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pseudo R-square</td>
<td>0.189</td>
<td>0.287</td>
<td>0.108</td>
<td>0.163</td>
</tr>
<tr>
<td>N (# Location Choices)</td>
<td>259</td>
<td>350</td>
<td>1,029</td>
<td>2,701</td>
</tr>
<tr>
<td># of Offenders</td>
<td>255</td>
<td>339</td>
<td>834</td>
<td>2,509</td>
</tr>
</tbody>
</table>

**NOTES:**

OR=odds ratio; standard errors clustered within offenders (not shown).

* p < .05 (two-tailed).

¹ Crime rate matches offense type being modeled (e.g., homicide rate for homicide model).
Table 4.7. Results from conditional logit models examining history and location suitability effects on UCR Part I property crime location choices in the city of St. Louis (2017-2018), by offense type.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Burglary OR</th>
<th>Larceny OR</th>
<th>Motor Vehicle Theft OR</th>
</tr>
</thead>
<tbody>
<tr>
<td>History Effects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Offender Previously Chose</td>
<td>15.295*</td>
<td>14.704*</td>
<td>6.275*</td>
</tr>
<tr>
<td>Co-offender Previously Chose</td>
<td>4.303*</td>
<td>1.649*</td>
<td>6.178*</td>
</tr>
<tr>
<td>Spatial Proximity to Suspect Home</td>
<td>1.234*</td>
<td>1.174*</td>
<td>1.155*</td>
</tr>
<tr>
<td>Community Structure</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Residential Population</td>
<td>1.001*</td>
<td>1.001*</td>
<td>1.001*</td>
</tr>
<tr>
<td>% Young Males (age 15-24)</td>
<td>1.004</td>
<td>0.974*</td>
<td>0.996</td>
</tr>
<tr>
<td>Racial Heterogeneity Index</td>
<td>1.026</td>
<td>1.020</td>
<td>1.053*</td>
</tr>
<tr>
<td>Disadvantage Index</td>
<td>1.006</td>
<td>1.117*</td>
<td>1.097</td>
</tr>
<tr>
<td>Land Use and Risky Facilities</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Land Use Diversity Index</td>
<td>0.962</td>
<td>1.019</td>
<td>0.984</td>
</tr>
<tr>
<td># of Secondary Schools</td>
<td>1.003</td>
<td>1.004</td>
<td>1.116</td>
</tr>
<tr>
<td># of Bars</td>
<td>1.022</td>
<td>0.972</td>
<td>1.027</td>
</tr>
<tr>
<td>Social Controls</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>311 Call Rate (x100)</td>
<td>1.419*</td>
<td>1.114</td>
<td>0.632</td>
</tr>
<tr>
<td>Arrest Rate (x100)</td>
<td>1.007</td>
<td>1.004</td>
<td>0.999</td>
</tr>
<tr>
<td>Police Activity (x100)</td>
<td>0.995</td>
<td>1.046*</td>
<td>0.981</td>
</tr>
<tr>
<td>Unobserved Suitability</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crime Rate (x100)</td>
<td>1.038*</td>
<td>1.007*</td>
<td>1.093*</td>
</tr>
<tr>
<td>Spatial Lag (x100)</td>
<td>1.011</td>
<td>0.997*</td>
<td>1.025</td>
</tr>
<tr>
<td>Model Statistics</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pseudo R-square</td>
<td>0.146</td>
<td>0.134</td>
<td>0.100</td>
</tr>
<tr>
<td>N (# of Location Choices)</td>
<td>1,057</td>
<td>3,404</td>
<td>727</td>
</tr>
<tr>
<td># of Offenders</td>
<td>797</td>
<td>2,658</td>
<td>679</td>
</tr>
</tbody>
</table>

NOTES:
OR=odds ratio; standard errors clustered within offenders (not shown).
* p < .05 (two-tailed).
1 Crime rate matches offense type being modeled (e.g., burglary rate for burglary model).
Discussion

Offenders are believed to engage in a multistage decision making process when committing crime: the first stage involves determining whether one is motivated and willing to commit crime; the second stage is selecting a location to search for targets and commit the crime (Brantingham & Brantingham, 1981, 1984; Brantingham & Brantingham, 1993; Clarke & Cornish, 1985; Cornish & Clarke, 1986; Wikström et al., 2012; Wright & Decker, 1996, 1997). Mainstream theory claims that locational suitability is the primary consideration of offenders during the second stage when they select an area to offend. I contend that the primary consideration is a history of offending in the location, either by oneself or one’s co-offenders. The discrete choice analysis presented above models the effects of both processes simultaneously, and suggests a combination of locational suitability, offender history, and co-offender history influences crime location choice.

These results contribute to a growing literature on how offenders actually make decisions about where to commit crimes. I argue that the findings suggest an important reinterpretation of past work regarding offending history effects (Bernasco et al., 2015; Lammers et al., 2015). Rather than “learning” that a prior crime site is a ‘good’ place to commit crime by offending there (Bernasco et al., 2015), the history effect should be interpreted as a status quo bias in the current study. This is because the present analysis controls for measured and unmeasured suitability influences, ruling out the notion that the offender chose the location based on suitability considerations. This means that offenders select prior crime locations (the status quo option) rather than other places that are more “suitable” for the offense. This status quo bias is consistent with work in
behavioral economics (Kahneman et al., 1991; Samuellson & Zeckhauser, 1988). Similar to the arguments in that literature, this effect raises concerns about whether mainstream decision making models (for example, Brantingham & Brantingham, 1993; Clarke & Cornish, 1985) represent how offenders actually make decisions, even if they make logical sense as models of how offenders should choose where to commit their crimes.

The history effects observed in this study also questions a long tradition of asking offenders themselves about how they make decisions when committing crimes. Offenders across a wide variety of qualitative studies define place factors or cues that they perceive to indicate whether the area is suitable for crime (Bernasco, 2013; Rengert & Wasilchick, 1985; Repetto, 1974; Rossmo & Summers, 2019; St. Jean, 2008; Wright & Decker, 1996). Following interviews with active armed robbers in St. Louis Wright and Decker (1997) summarize the process saying that “first, [offenders] had to decide on a suitable area for their [target] search” (p. 73). They then go on to describe preferences towards selecting areas, for instance, that are easy to get to from their homes where they are familiar and know that residents are unlikely to report suspicious behavior.

Offenders often explain such preferences in regard to locational suitability, but rarely do they mention an inherent bias toward re-selecting previous crime sites. This implies a discrepancy between what people say they do and what they actually do. It also lines up with what behavioral economists have already learned about decision making. In their seminal article on status quo bias, Samuelson and Zeckhauser (1988) describe that “in the debriefing discussions following the experiments, subjects expressed surprise at the existence of the bias. Most were readily persuaded of the aggregate pattern (and the reasons for it), but seemed unaware (and slightly skeptical) that they personally would
fall prey to this bias” (p. 9, emphasis in original). Offenders may similarly be unaware that they are influenced so heavily by history, to the point that they forego more optimal options.

The findings also contribute to the large literature on co-offending and the social network dimension of criminality. Co-offenders are known to influence others in their crime network, by generating willingness to engage in crime (McGloin & Nguyen, 2013), influencing the types of offenses to commit (Thomas, 2016), and even increasing risk of being victimized (Papachristos et al., 2012). The present study demonstrates that co-offenders also influence where offenders choose to commit their crimes. The exact mechanism underlying this co-offender history effect is not discernible from the present study. One possibility is that offenders tell others in their network about places they have offended. Active burglars in St. Louis described how receiving a tip was one consideration in choosing a target (Wright & Decker, 1996). While these tips sometimes came from those who may not actually engage in burglary themselves, this communication pathway may explain how co-offender history affects location selection, by establishing the area as a status quo alternative in others’ future decisions.

One notable finding with regard to co-offender history is how recency greatly increases the effect on re-selection. Prior work shows that crimes cluster in space and time in a way that suggests that one crime event substantially increases the likelihood of another event nearby for a short period of time (Loeffler & Flaxman, 2018; Mohler et al., 2011; Short et al., 2010; Short et al., 2008; Short et al., 2009). Given the large co-offending history effect (and relatively small offender history effect), it is more likely that the crime boosts observed in micro-temporal crime patterns are driven largely by
different offenders within the same crime network, rather than a flurry of repeat crimes by the same offender. If this is the case, the response to emerging crime hot spots should consider how the choice to commit a crime in that location is likely to spread quickly to others within the crime network responsible for the initial crimes.

**Limitations.** The data used to address the key research questions possess several strengths, but the limitations of using police data for measuring crime are well known in criminology (Biderman & Reiss Jr, 1967; Klinger & Bridges, 1997; Lauritsen et al., 2016). It is believed that crimes known to police underrepresents actual occurrences which produces a ‘dark figure of crime.’ While this may be a reasonable critique of using police records for descriptive purposes, there is also evidence that official data tend to trend with alternative sources (Blumstein et al., 1991). Convergence of data sources tends to be higher in urban areas (Berg & Lauritsen, 2016) and in more recent periods (Lauritsen et al., 2016). The analyses were conducted in an urban environment for the recent 2017-2018 period and can be assumed a representative sample of the distribution of crime and thereby produce population-level estimates of effects.

One could similarly critique the detailed incident data as an under-representation of the true underlying co-offending structure. In particular, it is possible that individuals associated with offenders, and therefore part of their social network, will not be present in the same incidents known to police or connected to the individual in some other observable way. Further, we can assume that only some of the criminal activity in which offenders are involved will be captured in the official crime data. Again, this is problematic if crimes known to the police are not representative of the distribution of actual criminal activity even if undercounted; bias is only consequential if missingness is
correlated with the outcomes of interest. This is difficult to assess without additional measures of social network ties from alternative sources, such as surveys or qualitative work (Campana, 2016; Decker et al., 2014). The analysis of co-offending was conducted as if the observed structure derived from incident data is incomplete, but still representative of the true underlying structure.

Beyond data limitations, one limitation to the analysis of crime location choice is limited treatment of the model assumption known as the “independence of irrelevant alternatives” property. It states that the choice probabilities for any two alternatives is independent from the utility of any other alternatives (Ben-Akiva & Lerman, 1985; Bernasco, 2010a). In the present context, this means that the model evaluates the probability that location A is chosen over location B, without regard for location C. Variations of the basic discrete choice model such as the competing destinations model could be used to model dependencies among alternatives rather than assume them away (Fotheringham et al., 2000).

Relatedly, the conditional logit model assumes that offenders consider all block groups in the city when deciding to commit a crime. Offenders probably only consider a select sample of locations in reality. Alternative specifications of the model involve designating which alternatives are among the choice set in any given decision, so that irrelevant alternatives are not considered (Bernasco, 2010a). But this would involve knowing which places each individual offender considers. Future research should examine ways to approximate the choice set, such as including only those areas within a given offender’s awareness space.
Alternatively, the nested logit model could be used if one is willing to assume that offenders first select a large general area before selecting a smaller specific area to search for targets. The nested logit model could then be used to examine how offenders select the specific area to search for targets, from within the larger area they are presumed to have selected (Bernasco, 2010a). For example, the choice set would then contain all block groups within the tract they selected, omitting block groups outside of that for the decision. Justification and examination of this model specification is left to future work.

Another limitation to the discrete choice framework is that it is assumed that if the observed crime event did not occur where in the observed location that it would have occurred somewhere else (i.e., the probability of displacement must be 1.0). The goal of the model is to understand why the offender chose the crime location over alternatives, rather than understand why the offender chose to commit crime in the first place. This limitation is exacerbated in the present context, because some mechanisms of path dependence such as retaliation expect that motivation for committing crime (e.g., retaliating against an aggressor) is dependent upon earlier crime occurrences. It is difficult to establish dependence among crime events without having extensively detailed incident information that directly links crimes to one another via some mechanism of positive feedback (for one example, see Kubrin & Weitzer, 2003b). Although quantitative accounts suggest that dependencies exist (Anderson, 1999; Jacobs & Wright, 2006; Wright & Decker, 1997), quantitative treatment of the research question is often restricted to theoretical expectations and correlations among variables. Further qualitative methods could be useful for identifying other possible mechanisms and operationalizing constructs in a more definitive way.
Conclusion

This chapter used data from St. Louis, Missouri to test for status quo bias in offender decision making. The results showed that offenders are more likely to choose to commit their crimes in places where they or their co-offenders have offended before. These effects were observed while controlling for a robust set of control variables intended to measure variation in locational suitability. The large effect sizes suggest that status quo alternatives can be selected even if more optimal crime sites are available. One implication is that decision making models of mainstream theory are inaccurate, or at least incomplete, descriptions of actual offender behavior and should be modified to include offending history as a powerful influence in crime location choice.

Status quo bias is a microscopic mechanism that serves as a foundation for the path dependence process outlined in this dissertation. Having observed the status quo bias, the next chapter considers the macroscopic implications of this mechanism for aggregate crime patterns. Crime location re-selection means there is positive feedback in crime. This positive feedback generates nonlinearity in aggregate patterns, making outcomes unpredictable and sensitive to small, chance events (Arthur, 1994). An agent-based model is used in the next chapter to understand the implications of the status quo bias for geographic crime patterns.
Chapter 5. Macroscopic Consequences of Status Quo Bias

The previous chapter demonstrated that offenders have a status quo bias when selecting locations to commit crime, causing them to re-select places they or their co-offenders have selected before. This mechanism stands in contrast to mainstream theory that claims the importance of place suitability factors, implying that conventional models should be modified to better fit actual decision making. This chapter goes beyond the microscopic choice process to examine the macroscopic implications of status quo bias.

As explained in Chapter 3, the status quo bias is one potential mechanism of positive feedback or path dependence in aggregate crime patterns. Over time, re-selection of the same place(s) will cause the crime problem to grow increasingly large. This path dependence process eventually causes patterns to become locked-in, making it difficult for change to occur (Arthur, 1994). The nonlinear attribute of path dependence makes patterns unpredictable and difficult to study using conventional methods. Simulation modeling is one way to circumvent this challenge. This chapter uses simulation modeling as a “tool for thought” (Waddington, 1977) to represent alternative hypotheses about the crime location choice process. Then, experiments are conducted on the model to examine how implications of those alternative hypotheses play out in aggregate patterns (Dowling, 1999; Edmonds & Hales, 2005; Morrison, 2009; O’Sullivan & Perry, 2013).

Computer simulation has become a useful experimental approach in the criminology literature when empirical observation is not possible or ethical (Birks et al., 2012; Brantingham & Brantingham, 2004; Groff, 2007). The current study concerns the implications of alternative hypotheses about offender decision making. The ideal comparison, then, is the difference between two possible worlds: one where status quo
bias is absent (control condition) and one where status quo bias is at play (experimental condition). The only realistic way to observe this comparison is to artificially simulate crime patterns under alternative decision making assumptions.

The specific type of simulation used here is an agent-based model which was originally popularized by Epstein and Axtell (1996) (see also Epstein, 1999, 2002) and has been a simulation model of choice in criminology (Birks & Davies, 2017; Groff, 2007; Groff et al., 2019; Johnson & Groff, 2014; Malleson et al., 2013). This approach creates an artificial environment populated by autonomous agents who interact according to simple prescribed rules. These local interactions generate macroscopic regularities “from the bottom up” (Epstein, 1999). Experimental manipulation of the interaction rules examines how alternative assumptions affect outcomes. This approach creates the perfect counterfactual, where all conditions are identical between control and experimental conditions so that any differences can be attributed directly to the interaction rule being manipulated.

The next section describes the agent-based model that was built to represent the crime location choice process and produce the “data” used to test hypotheses. Many scientific fields recognize the need to use standard protocols to document models so that findings can be replicated by others (Schmolke et al., 2010), and criminology is no exception (Pridemore et al., 2018; Savolainen & VanEseltine, 2018). In the context of computerized model building, Grimm et al. (2006) developed the overview, design concepts, and details (ODD) protocol that serves as a standard for describing agent-based models (Grimm et al., 2010; Groff et al., 2019). I present the model with the ODD
protocol in mind, but without creating an unnecessarily lengthy description, per the revised protocol of Grimm et al. (2010).

**Model Overview**

Table 5.1 summarizes a large amount of information about model inputs and outcomes. The rationale for selecting a particular value for a parameter is provided. Parameters are derived from empirical data or theory when available. Each parameter and design concept will be further described in the sections that follow. The model is built in Netlogo 6.1.1 and data are imported to Stata 15.1 for outcome analyses.

**Purpose.** The purpose of this model is to test hypotheses regarding the macroscopic effects of status quo bias in crime location choice. The model allows the researcher to experimentally change the offender decision making calculus to include, at varying levels, the influence of past crime locations on where an offender chooses to commit their crimes.

**Definitions.** Terms are defined as they are used to describe the model.

- *Model* refers to the entire agent-based modeling environment, including the grid cells, agents, and code.

- *Run* refers to one realization of the simulation model from start to finish. Multiple runs are simulated and summarized to describe representative outcomes.

- *Condition* is a set of specific model parameters that determine agent actions in each run of the model.
Table 5.1. Agent-based model parameters.

<table>
<thead>
<tr>
<th>Parameter/Outcome</th>
<th>Model Specification</th>
<th>Rationale</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Global Parameters</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model environment size</td>
<td>19 × 19 grid = 361 grid cell areas</td>
<td>Chapter 4 in this study reports 360 block groups in city of St. Louis.</td>
</tr>
<tr>
<td>Model runs per experiment condition</td>
<td>45</td>
<td>Power analysis indicates 45 paired model runs are necessary to observe a medium-sized mean difference ($d_z = 0.5$) between two dependent (matched) groups (assuming $\alpha=0.05$ and $1-\beta=0.95$).</td>
</tr>
<tr>
<td>Model tick time period</td>
<td>1 year</td>
<td>Conforms with simulated offending rates. Intra year outcomes are not assessed.</td>
</tr>
<tr>
<td>Model termination</td>
<td>30 years (ticks)</td>
<td>Balance between statistical power and processing time.</td>
</tr>
<tr>
<td>Number of offender agents</td>
<td>1,710 agents at all times</td>
<td>Eliminates data sparseness issues. Also ensures there are never more places than crimes, which would require additional adjustments to outcome measures (Bernasco &amp; Steenbeek, 2017) and creates other data sparseness issues.</td>
</tr>
<tr>
<td>History effects</td>
<td>Probability an offender becomes locked-in to a historical crime site varies by experiment condition: $0.0000$ (null effect), $0.3333$ (weak effect), $0.6666$ (strong effect)</td>
<td>Discrete choice model estimates from Chapter 4 indicate strong effect ($0.6666$) is justified by empirical data.</td>
</tr>
<tr>
<td>Number of hotspots targeted by intervention</td>
<td>45</td>
<td>Power analysis indicates 45 areas (12.5 percent of the total area) should be targeted by the intervention to observe a medium size ($d=0.5$) pre-post effect in treatment areas (assuming $\alpha=0.05$ and $1-\beta=0.95$).</td>
</tr>
<tr>
<td>Place-based intervention effects</td>
<td>Reduce location suitability at target grid cells by 50%</td>
<td>Arbitrary. Alternative values to be assessed in sensitivity modeling.</td>
</tr>
<tr>
<td>Person-based intervention effects</td>
<td>Eliminate target locations from offending history choice set</td>
<td>Represents disruption of individual status quo bias.</td>
</tr>
<tr>
<td>Parameter/Outcome</td>
<td>Model Specification</td>
<td>Rationale</td>
</tr>
<tr>
<td>-------------------</td>
<td>---------------------</td>
<td>-----------</td>
</tr>
<tr>
<td>Network-based intervention effects</td>
<td>Eliminate target locations from co-offending history choice set</td>
<td>Represents disruption of status quo bias from co-offenders</td>
</tr>
<tr>
<td><strong>Grid Cell Parameters</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Location suitability</td>
<td>Voter model (Weidlich, 1971) applied to random values drawn from exponential distribution to create patchy environment where crime suitability is highly concentrated</td>
<td>Social-environmental characteristics create patchy clusters of similarity in urban environments (Brantingham &amp; Brantingham, 1981; Lynch, 1960)</td>
</tr>
<tr>
<td><strong>Offender Parameters</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>Offenders enter model at age 12 and die at age 70. Age increases by one year at each model tick.</td>
<td>Most offenders “age-out” of crime by age 70 (Sampson &amp; Laub, 2003). Individuals believed to offend at different rates throughout the life course (age-crime curve), and different trajectories have been observed. Empirical estimates taken from Sampson and Laub (2003) are used and align with observed data in Chapter 4.</td>
</tr>
<tr>
<td>Annual rate of offending</td>
<td>Determined by age and offending trajectory (e.g., high rate chronic, classic desister)</td>
<td></td>
</tr>
<tr>
<td>Number of co-offending groups</td>
<td>Initial number of groups calculated as 0.13 × offender population (1,710), resulting in 220 mutually exclusive groups. New offenders join an existing group with 0.987 probability and create new group with 0.013 probability.</td>
<td>Co-offending data in St. Louis suggest there are 0.13 co-offending groups represented by each offender.</td>
</tr>
<tr>
<td>Routine activity nodes</td>
<td>Home node and 4 activity nodes</td>
<td>Per (Golledge &amp; Spector, 1978), consistent with past research (Birks et al., 2012; Groff, 2007) 300 “steps” ensures agents are able to move to each of their activity nodes to establish awareness</td>
</tr>
<tr>
<td>Size of awareness space</td>
<td>Varies randomly by offender. Created by moving between activity nodes for total of 300 grid cell units</td>
<td></td>
</tr>
</tbody>
</table>
Model parameters and scales. Model time steps represent one year of real time. This has implications for the number of crimes that each offender commits within a time step and reduces the need to model seasonality in offending. This also means that crime patterns cannot be measured for increments smaller than one year (e.g., monthly, weekly).

The model space is a $19 \times 19$ grid of square cells with each cell representing an area in the city.\textsuperscript{10} The space is not toroidally wrapped, meaning that passing the eastern edge of the space does not place the agent on the western side.\textsuperscript{11} Each grid cell is characterized by a variable representing locational suitability. Location suitability is a continuous variable ranging from 0 (low suitability) to 1 (high suitability) indicating the combined level from all place suitability factors. Figure 5.1 shows what the modeling environment looks like in one realization of the model (see below for details about creating the patchy configuration). Each grid cell is shaded according to the level of locational suitability, representing the combined influence from all place-based suitability factors (i.e., “composite suitability” from Chapter 2).

\textbf{Figure 5.1.} Agent-based modeling environment showing $19 \times 19$ grid cells ($N=361$) each characterized by a value for locational suitability. Lighter shaded areas have high suitability, darker shaded areas have lower suitability.

\textsuperscript{10} The $19 \times 19$ cell area was selected because there are a total of 361 grid cells, which is close to the 359 block groups in the city of St. Louis, Missouri.

\textsuperscript{11} Toroidal wrapping eliminates edge effects, but distances are much easier to compute without wrapping.
The model environment is populated by mobile agents representing individual offenders. Other entities in the model include activity nodes, activity “footprints,” and crimes. Offenders move between activity nodes and choose to commit crimes at target locations based on prescribed decision making rules. Offenders are characterized by the following state variables:

- **Age** is an integer variable representing the offender’s age in years. All offenders enter the model at age 12 and die at age 70.
- **Home node** stores the offender’s home location and is selected as a random location in the environment when they enter the model. Home locations are fixed for the duration of the simulation.
- **Activity nodes** is a list of four randomly chosen locations that an offender uses to move and create their awareness space.
- **Co-offending network** is an integer ID number representing which co-offending group the offender belongs to.
- **Offending trajectory** holds information about which of six different offending trajectories the offender will assume. The trajectories are derived from empirical estimates provided by Sampson and Laub (2003).
- **Offending propensity** is an integer value representing the number of crimes the offender will commit during the current year. This value is computed from the offender’s age and offending trajectory, per empirical estimates provided by Sampson and Laub (2003).
- **Crime history** is a list of locations where the offender has previously committed crimes.
• *Locked-in* is a Boolean true/false variable indicating whether the offender is locked-in to selecting a crime location from their offending history or their co-offenders offending history.

Each offender is associated with five stationary entities that represent activity nodes. One node is designated as their home node. When offenders enter the model, their activity nodes are randomly placed in the environment and one is selected as the offender’s home. Offenders then move among these nodes to represent routine activity behavior. While moving through the environment, the offender leaves behind activity ‘footprints’ (i.e., stationary entities) that represent areas in the offender’s awareness space. Both the activity nodes and routine activities contain a state variable that indicates which offender they belong to.

Crimes are stationary entities that mark the location of a crime committed by an offender. To reduce processing time, information stored in each crime is exported to a spreadsheet at the end of each year and crimes are removed from the model. Each crime includes details about the experimental or control conditions at the time the crime was committed, information about the offender who committed the crime (e.g., ID, age, co-offending network), and details about the grid cell where the crime occurred. The exported list of crimes is analyzed at the end of the simulation.

Behaviors of the offenders are governed by several global model parameters as follows:

• *History effect* ranges from 0.0 (no history effect) to 1.0 (history is all-powerful) and represents the probability that an offender becomes locked-in to selecting a crime location from their offending history. When the
history effect is set to 0.0, offenders do not have any status quo bias. If the
history effect is set to 1.0, the offender randomly selects a location for
crime from their offending history each time they commit a crime (after
the first crime). Values between 0.0 and 1.0 indicate a chance of becoming
locked-in to selecting a historical crime location.

- *Co-offender history effect* similarly ranges from 0.0 (no effect) to 1.0
  (history is all-powerful) and represents the probability that an offender
  becomes locked-in to selecting a crime location from their co-offenders’
  offending history.

- *Place-based intervention* is a Boolean parameter indicating whether a
  place-based intervention will be enabled during the model run.

- *Person-based intervention* is a Boolean parameter indicating whether a
  person-based intervention will be enabled during the model run.

- *Network-based intervention* is a Boolean parameter indicating whether a
  co-offending network-based intervention will be enabled during the model
  run.

- *Random seed* is a value ranging from -2,147,483,648 to 2,147,483,647 that
  sets the seed of the pseudo-random number generator. Note that the seed is
  set to the same number for each of the conditions within an experiment so
  that the only differences between experimental and control conditions are
  the history effects governing crime location choice. For instance, the
  structure of location suitability in the environment is created using a series
  of random numbers. The seed used in the random number generator
therefore determines the structure of the environment. Using the same seed will re-produce the same environment, so using the same seed in the control and experimental conditions over many runs creates a “paired sample” where only the offender choice calculus is different between conditions.

- *Offender birth rate* is the number of new offenders added to the model during each step (year).

**Process Scheduling**

The model proceeds in several steps:

1. Initialize environment.

2. Initialize offenders.

3. Initialize global parameters.

4. Burn-in period.

5. Model iterations.
   a. Add new offenders.
   b. Commit crimes.
   c. Update offender and environment state variables.
   d. Export crimes and environment data to spreadsheet.
   e. Delete crimes.
   f. Increment one year and repeat.
Design Concepts

The model implements multiple criminological processes to test the hypotheses of interest. The model is admittedly complex, but I argue below that including each process is necessary to create a sufficient level of model realism. Each model component is meant to represent the essential features of real-world interactions, not necessarily replicate them in every detail. The following sections describe how each core concept is represented in the model.

Uneven distribution of locational suitability. A key feature of interest is how offender agents interact with the environment when deciding to commit crime. Social and environmental characteristics are distributed unevenly in urban environments, sometimes described as an “urban mosaic” pattern (Brantingham & Brantingham, 1981; Brantingham & Brantingham, 1975). The confluence of various social and environmental features creates areas that are suitable for crime to occur (Cohen & Felson, 1979), which is assumed to be highly concentrated in space. A stepwise process is used to randomly generate an environment that is patchy with concentrated areas of high locational suitability, combining multiple approaches described in O'Sullivan and Perry (2013).

First, locational suitability values are randomly assigned to each grid cell according to an exponential distribution with mean = 1 to create an uneven distribution of suitability. Next, a voter model (Weidlich, 1971) is implemented so that, during each of 30 iterations, all grid cells are re-assigned in random order the value of one randomly selected neighbor. This process creates a patchy configuration. Then, the grid cells are re-assigned the average value of their four neighbors to slightly diffuse the patchiness across space and increase heterogeneity. Finally, the values are re-scaled so they range from 0.0
to 1.0. This is done by subtracting the minimum value from the grid cell’s value and dividing the result by the range \((\frac{x-x_{min}}{x_{max}-x_{min}})\). Figure 5.2 shows a few realizations of this process to initialize location suitability in the environment.

**Routine activities and awareness space.** Routine activities are important for offending behavior because they create an awareness space within which offenders feel familiar and therefore more comfortable committing crime (Brantingham & Brantingham, 1981, 1984; Brantingham & Brantingham, 1993). Offenders are also theorized to come into contact with targets for crime in the course of noncriminal activities, such as traveling to work or school (Felson, 1994; Felson & Cohen, 1980). A routine activity/awareness space is established for each offender when they enter the model.

The literature on human activity patterns suggests individuals engage in anchor-based navigational movement (Golledge & Spector, 1978). Consistent with prior work (Birks et al., 2012), random locations are selected in the environment to represent a home location and four activity nodes. The agent begins at their home node and randomly moves toward the location in 1-unit steps following a simple shortest path algorithm (Dijkstra, 1959). Upon arrival at the activity node, the agent turns towards home (with probability 0.8, per Birks et al., 2012) or towards another randomly chosen activity node and moves towards that location. The process is repeated until the offender has traveled a total of 300 units (grid cells are 1 × 1 units).

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12 Four activity nodes are used following Birks, D., Townsley, M., & Stewart, A. (2012). Generative explanations of crime: using simulation to test criminological theory. *Criminology, 50*(1), 221-254. who found that model results are robust to different numbers of routine activity nodes.
Figure 5.2. Three realizations of a patchy environment with concentrated suitability.

Each time the offender takes a step, the agent creates an activity “footprint” representing awareness at that location. These activity footprints are stored by each offender and used when selecting target crime locations. Areas with more awareness are more likely to be selected by an offender than other areas. Note that no additional awareness is generated after the offender initially enters the model and establishes their awareness space. Figure 5.3 shows an example of offenders (cyan) establishing awareness space (yellow “footprints”). In the first image (5.3.1) the offender is standing at their home location and traveled back and forth among their four activity nodes represented as orange flags. The yellow footprints indicate their resulting awareness space. It is clear that this offender frequently traveled to and from the southwestern most node because there is a greater density of footprints. Occasionally, the offender appears to have traveled between nodes without going home first, but they most often return home once arriving at a node. The second image (5.3.2) shows the case with 20 offenders
and their overlapping awareness spaces. Areas with denser activity patterns should be expected to have more crimes.

![Figure 5.3. Offender routine activities and awareness space represented in the agent-based model. (1) N=1 offender. (2) N=20 offenders (icons reduced in size).](image)

**Age-crime curve and offender desistance.** New offenders are added to the model during each time step (year). This simulates the continuous addition of individuals into the potential offender pool. Offenders enter the model at age 12 and die at age 70. A total of 1,140 offenders are present in the model at any given time and 20 new offenders are added each year (57 years alive × 20 offenders).

Each offender is assigned several characteristics upon entering the model. The first is an offending trajectory that will govern the number of offenses they are expected to commit each year, given their age. Sampson and Laub (2003) published results from one of the few studies to provide empirical data on offending for the same individuals.
over the entire life-course. Group-based trajectory models were used in their study to categorize individuals into offending trajectories, resulting in six mutually exclusive groups (see Figure 11 in original study, page 582). The likelihood that an offender is placed into each of the six groups is based on the respective proportion of offenders in Sampson and Laub’s sample in each group. The estimated offending trajectories and respective proportions in the population are shown in Figure 5.4.

Figure 5.4. Age-based offending propensities for different offending trajectories, derived from empirical estimates (Sampson & Laub, 2003).
When offenders enter the model they are assigned an integer value indicating the number of crimes they will commit that year. The value is based on the offender’s current age and their predicted rate of offending for their trajectory, based on Sampson and Laub (2003). Suppose, for example, the agent is age 24 and classified as a moderate rate chronic offender so that their predicted rate of offending is 1.5. The number of offenses they will commit during that year will be a random integer drawn from a Poisson distribution with mean = 1.5.

Co-offending. Co-offending networks are believed to be influential in offending (Faust & Tita, 2019; McGloin & Nguyen, 2013). Yet, there is little research estimating how many co-offending groups exist in a city at any given period of time. Offenders are each assigned to a co-offending network so that co-offender crime history can influence behavior. The model assumes that there are about $C$ unique co-offending groups, where $C$ equals the number of offenders in the model multiplied by 0.13. The first $C$ offenders who enter the model are assigned to their own co-offending group. Thereafter, every offender agent who enters the model is randomly assigned to the co-offending group of another offender, with probability proportional to proximity. This assumption is based on the idea that co-offending group membership is tied to spatial territories, sometimes termed “set spaces” (Tita et al., 2005), as well as routine encounters with others who live close by. In either case, it seems intuitive to place agents in groups with those who live nearby them. Given that co-offender networks will tend to disappear as offenders die, new offender agents entering the model have a probability of 0.013 of creating a new co-offender group rather than join an existing group, to retain roughly the same number of co-offending groups in the model at all times.
Specifying roughly $C$ co-offending groups is consistent with empirical data from St. Louis, Missouri. A network analysis was conducted of all offenders who committed UCR Part I crimes during 2017-2018. A total of 10,082 offenders are identified in the sample. A 10,082 by 10,082 network matrix was created where cells represented a co-offending tie between two individuals involved together in an incident. Next, a component analysis was conducted using the \texttt{nwcomponents} command in Stata 15.1 (Grund, 2015) to identify sets of nodes (offenders) that are connected only to each other (through co-offending). The analysis resulted in 1,367 mutually exclusive components or co-offending groups. This represents a rate of 0.13 co-offending groups per offender.\textsuperscript{13}

**Crime location choice.** The central process of interest is how offenders make decisions about where to commit their crimes. Offenders are assumed to follow a multistage choice process by first deciding they are motivated to engage in crime before deciding where to search for crime targets (Brantingham & Brantingham, 1981, 1984; Brantingham & Brantingham, 1993; Clarke & Cornish, 1985; Cornish & Clarke, 1986; St. Jean, 2008; Wikström et al., 2012; Wright & Decker, 1996, 1997). Consistent with other studies of this type (e.g., Birks et al., 2012; Groff, 2007), offenders are assumed to be motivated. They will commit a given number of crimes, as determined by their age and offending trajectory at each model step (see above discussion of offending rates). This means that motivation to commit crimes is exogenous in the model.

The second stage of selecting a location for crime is the focus of the model. When crime commission commences, offenders are selected randomly to commit a crime until all offenders who will commit crime during that year have committed one crime. This

\textsuperscript{13} The largest co-offending group included 1,354 offenders.
process is repeated until all offenders have committed all their crimes for the given year. Each offender selects a location to commit crime based on selection criteria determined by the experimental condition. Each condition is described as follows:

**Null history effects.** Crime location decision making in this condition is driven by locational suitability and the offender’s awareness of areas in the environment. Offenders select a location from the set of activities in their awareness space with probability proportional to locational suitability at each location. The choice set does not contain all possible areas in the city (as assumed in discrete choice modeling). Rather, the choice set contains only those locations where the offender travels during their routine activities, so that locations outside the offender’s awareness space have zero probability of being selected. Locations where the offender has passed more frequently, and those with higher suitability, are more likely than other locations to be selected.

**Weak history effects.** Crime location decision making in this condition is a function of the offender’s awareness space and either locational suitability or history. Offender history and co-offender history effects are each set at 0.3333. This means that offenders determine whether they are “locked-in” to their own offender history with probability of 0.3333 or their co-offenders’ history with probability of 0.3333, or both with probability equal to $0.3333 \times 0.3333 = 0.1111$. If the offender is not locked into either history, they proceed as in the null effects condition. If the offender determines to be locked-in to history, the choice set is a list of past crime locations and one location is selected from the list with each having equal probability.

Note that if no crimes have been committed by the offender (or their co-offenders), they cannot become locked-in to history and they revert to the same process
as specified in the control condition. First-time offenders, for instance, will never be locked-in to their own offending history but can still be locked-in to history of their co-offenders. Offenders with no one in their co-offending network cannot be locked-in to co-offender history. This implies that locational suitability will have some influence on crime location choice even when history effects are present.

Strong history effects. This experimental condition is identical to the “weak effects” condition, except the history effects are set at 0.666. This means that offenders (who have crime history) will become locked-in to their own history with probability equal to 0.666, locked-in to their co-offenders’ history with probability 0.666, or locked-in to both with probability equal to $0.66 \times 0.66 = 0.4443$.

Notes on cutoff values. The cutoff values of 0.333 and 0.666 were selected to represent cases where history has weak and strong influence respectively. The results presented in the previous chapter from discrete choice models suggested that the odds of selecting a historical crime location over other locations were greater than 10 times higher for offender history and greater than 3 times higher for co-offender history (main model, Table 4.3).

Mathematically speaking, odds ratios are ratios of odds, and odds are ratios of probabilities. If the probability of selecting a given site is 0.666, then the odds of selecting that site over the odds of selecting a different site are equal to $4$ ($OR = \frac{0.666}{0.333} = \frac{2}{0.5} = 4$). This means that selecting 0.333 as a cutoff value is conservative for both effects, and selecting 0.666 as a cutoff is conservative for the offender history
effect and about right for the co-offender history effect. Future models could specify more exact values from the discrete choice model estimates, incorporating much higher specificity of history effects in the model. This model uses 0.33 and 0.66 as two benchmark options to reduce complexity and avoid overfitting the model to data.

**Intervention effects.** One implication of status quo bias and positive feedback processes is that aggregate patterns of behavior become locked-in and resistant to change. In the present context, this resistance means that changes in locational suitability may not affect an offender who has established a pattern of behavior. Changes to locational suitability in an area where an individual commits their crimes may not affect their choices if they are locked-in, but it may affect others who have not established offending history there. The efficacy of place-based interventions that target locational suitability factors, such as hot spots policing (Weisburd et al., 2017) or crime prevention through environmental design (Jeffery, 1977; Taylor & Gottfredson, 1986), are dependent upon the strength of history effects and the number of offenders responsible for crimes at the target locations.

On the other hand, person-based interventions may be useful for targeting the history effects that cause offenders to re-select prior crime sites. These interventions could take many different forms. They could involve incapacitating individuals responsible for committing crimes at the target location (e.g., arrest) or attempting to increase their risk perceptions (e.g., focused deterrence). Research suggests that these

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14 To get an odds ratio of 10, the probability of selecting a prior crime site would need to be more than 0.75

\[
\frac{\text{O.R.}}{\overline{\text{O.R.}}} = \frac{0.75/0.25}{0.33/0.33} = 9.
\]
person-based interventions are effective at reducing targeted crime problems (Braga, 2008; Braga et al., 2018; McGarrell et al., 2006; Papachristos et al., 2007).

Alternatively, interventions that target the network dimension of history effects may be another promising alternative. Network effects can have cascading effects, influencing many offenders and their crimes. Interventions that attempt to disrupt the transmission of status quo options among co-offenders may generate “exit from lock-in.” Social network-based interventions used to decrease offending behavior appear to be promising (Morselli, 2009, 2013; Morselli & Petit, 2007; Zhang, 2014). An outstanding question concerns how network disruption affects crime levels at target locations.

Details

This section describes relatively minor details of the agent-based model that would be necessary for replication.

**Initializing offenders.** The process to initialize offenders includes adding 1,710 offenders to the model, 30 offenders at a time. This ensures that the simulation does not begin until 30 offenders of each age from 12-69 years old are present in the model. After model initialization, 30 new offender agents are added to the model each year of the simulation run as described above. Upon entering the model, the offender’s state variables are initialized, including establishing their awareness space, determining their offending trajectory, and assignment to a co-offender group. Roughly 220 co-offender groups are expected to be represented by the 1,710 offenders in the model at any given time.
Model Evaluation

A crucial process in using agent-based models is ensuring that the model represents target phenomena in the real world (Berk, 2008; Gilbert, 2019; O'Sullivan & Perry, 2013). The challenges to validating agent-based model outcomes in criminology are well known (Groff & Birks, 2008). For one, simulation models can sometimes struggle to differentiate effects from alternative mechanisms operating simultaneously at various scales (Manson, 2007). In the crime context in particular, data sources against which to compare model outcomes are wrought with issues well-known in the discipline (Maguire, 2002). Agent-based models include all crimes committed whereas empirical crime models include only a (nonrandom) sample of crimes known to police, for instance. This means that validating the model with data is a significant challenge.

Simulation modelers tend to rely on conceptual models and vague heuristics to validate models in the absence of ground truth benchmarks (Birks & Davies, 2017; Birks et al., 2012; Groff, 2007; Groff & Mazerolle, 2008; Liu & Eck, 2008). Examples of such heuristics might be that crime concentrates among a relatively small proportion of places (Weisburd, 2015), a few targets experience the majority of victimizations (Farrell et al., 1995), or the offender journey to crime is positively skewed. Results from a model are less trustworthy if, perhaps, crimes were evenly distributed across offenders than from a model where most crimes were committed by a few prolific offenders (Martinez et al., 2017; Spelman & Eck, 1989). As done in previous research of this kind, the base model was run under null conditions for 45 runs over a five-year simulation period. Model outcomes were evaluated against four well-known patterns in empirical crime data:
• Spatial crime concentration (Braga et al., 2017; Brantingham et al., 1976; Freeman et al., 1996; Johnson, 2010; Lee et al., 2017; Weisburd, 2015);

• Variation in offending across individuals and within individuals over the life course (Farrington, 2003; Laub & Sampson, 2003; Martinez et al., 2017; Moffitt, 1993; Sampson & Laub, 1995, 2003; Wolfgang et al., 1972);

• Stability and change in spatial crime patterns over time (Mohler et al., 2018; Mohler et al., 2011; Sherman, 1995);

• Positive skewness in the offender journey to crime (Rengert, 2004).

The model would not be considered a valid representation of key criminological processes if it was not able to generate these signature crime patterns (Epstein, 1999; O'Sullivan & Perry, 2013).

Results from the base model evaluation show that less than 17 percent of the locations experienced 50 percent of the crimes. The average age of the offender was 30.4 years old (SD=13.36). The average offender committed 2.79 crimes (SD=0.09) and the average standard deviation in offending frequency was 2.48 (SD=0.11). The average maximum number of crimes committed by an offender was 17.82 (SD=2.40) and the average skewness was 2.11 (SD=0.20). Finally, the average distance between the offender’s home and the crime (journey to crime) was 5.99 units (SD=4.17) with average skewness equal to 0.7 (SD=0.04).

Figure 5.5 shows simulated distributions for one run of the base model as a proof of concept. All distributions are positively skewed, loosely following conceptual models suggested in empirical research (Hirschi & Gottfredson, 1983; Lee et al., 2017; Martinez
et al., 2017; Rengert, 2004). Note also that the age and journey to crime distributions align with those observed in the St. Louis data shown in Figure 4.2. Taken together, these findings suggest that the model is a reasonable approximation of key criminological processes.

**Figure 5.5.** Simulated distributions from one base model run (N=2,136 crimes over 5 years).
Experimental design

An experimental design is used to test several hypotheses about the effects of status quo bias on aggregate crime patterns. A total of seven experimental conditions are used as shown in Table 5.2.

<table>
<thead>
<tr>
<th>Condition</th>
<th>History Effect</th>
<th>Strength</th>
<th>Offender</th>
<th>Co-Offender</th>
<th>Place-based</th>
<th>Interventions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Person-based</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Network-based</td>
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<tr>
<td>Experiment 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>Null</td>
<td>Null</td>
<td>Disabled</td>
<td>Disabled</td>
<td>Disabled</td>
<td>Disabled</td>
</tr>
<tr>
<td>2</td>
<td>Weak</td>
<td>Weak</td>
<td>Disabled</td>
<td>Disabled</td>
<td>Disabled</td>
<td>Disabled</td>
</tr>
<tr>
<td>3</td>
<td>Strong</td>
<td>Strong</td>
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<td>Disabled</td>
<td>Disabled</td>
<td>Disabled</td>
</tr>
<tr>
<td>Experiment 2</td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Null</td>
<td>Null</td>
<td>Enabled</td>
<td>Disabled</td>
<td>Disabled</td>
<td>Disabled</td>
</tr>
<tr>
<td>5</td>
<td>Strong</td>
<td>Strong</td>
<td>Enabled</td>
<td>Disabled</td>
<td>Disabled</td>
<td>Disabled</td>
</tr>
<tr>
<td>6</td>
<td>Strong</td>
<td>Strong</td>
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<td>Enabled</td>
<td>Disabled</td>
<td>Disabled</td>
</tr>
<tr>
<td>7</td>
<td>Strong</td>
<td>Strong</td>
<td>Disabled</td>
<td>Disabled</td>
<td>Enabled</td>
<td></td>
</tr>
</tbody>
</table>

**Experiment 1.** The first experiment compares the first three experimental conditions on outcomes measuring spatial crime concentration and temporal stability in crime hot spots. Three metrics are used for crime concentration. The first two measures are the percentages of places that account for 50 percent and 25 percent of the crimes that occur in a given period, respectively (Mohler et al., 2018; Weisburd, 2015). Crime is more concentrated when fewer places account for a larger percentage of the distribution. For simplicity I will refer to hot spots that account for 50 percent of the distribution as
“50 percent hotspots” and those that account for 25 percent of the distribution as “25 percent hotspots.” The third measure of crime concentration is the Gini index, which represents dispersion in the distribution. It is commonly used to study inequality (Gastwirth, 1972) but has also been proposed as a measure of crime concentration (Bernasco & Steenbeek, 2017). Higher Gini values indicate greater concentration.

*Hypothesis 1. Crime will be more concentrated when status quo bias has stronger influence on crime location choice.*

Three metrics will be used to assess temporal stability in crime hot spots. The first is a simple measure of the percentage of locations classified as crime “50 percent hotspots” from one time period to the next (Mohler et al., 2018). The second is the same, but for “25 percent hotspots.” The third measure involves computing the coefficient of variation to measure dispersion in the amount of crime that occurs in each grid cell area over the time series (Johnson & Bowers, 2008). The challenge with this measure of stability is that it is sensitive to zero crime counts. An area with zero crimes for 29 years and 1 crime in the last year will have a coefficient of variation equal to 5.48 (very unstable), while an area with 1 crime each year for 29 years and 2 crimes in the last year will have coefficient of variation equal to 0.177 (very stable).\(^{15}\) Johnson and Bowers (2008) show how the relationship between cumulative crime risk and the coefficient of variation forms an L-shaped pattern, with low crime areas having low stability and high crime areas having high stability. Because the impact of status quo bias is most important

\(^{15}\) An area with 100 crimes every year for 29 years and 200 crimes in the last year will have COV=0.177.
in high crime areas, the outcome computed in a given run will be the average coefficient of variation among any area which was ever designated as a “50 percent hotspot” over the run (see “50 percent hotspot” defined above).

**Hypothesis 2:** Crime hotspots will be more stable (locked-in) when status quo bias has stronger effects on crime location choice.

**Experiment 2.** The second experiment is designed to test the limits of path dependent “lock-in” to determine which types of crime reduction interventions can overcome positive feedbacks in offender decision making. In each condition, a sample of locations are subjected to the intervention and a pre-post comparison is made at target locations. Power analysis suggests that 45 areas should be targeted by the intervention in order to observe a medium size pre-post effect in treatment areas ($d=0.5$; assuming $\alpha=0.05$ and $1-\beta=0.95$). The efficacy of the interventions is evaluated using a simple pre-post comparison of total crime counts at the target locations. The intervention will occur at year 20 and the first ten years will be discarded (treated like a burn-in period).

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16 Concerns over displacement are ignored because offenders are guaranteed to select an alternative location. Future work should address whether these types of interventions have potential to cancel a crime that would have occurred otherwise, thereby reducing overall crime levels. For examples see Groff (2007); Weisburd et al. (2017).

17 The 45 target areas will represent 12.5 percent of the total grid space. Targeting 12.5 percent of a jurisdiction’s total land area would be considered quite large for real-world experiments. For instance, a hot spots policing experiment conducted in St. Louis targeted 32 hot spot areas in the city (Rosenfeld, Deckard, & Blackburn, 2014), representing closer to 1 percent of the city area. In a randomized controlled trial testing the effects of an urban blight remediation intervention, 73 lot clusters (about 365 lots) in Philadelphia were assigned to experimental conditions (Branas et al., 2018; Moyer, MacDonald, Ridgeway, & Branas, 2019); this intervention targeted less than 1 percent of the nearly 300,000 parcels in the city.

18 A more elaborate time series design is unnecessary given the ability to implement strict control over all aspects of the experiment. Each experimental condition is treated as a unique and perfect counterfactual.
preintervention period will be years 11-20 and the postintervention period will be years 20-30. Each intervention is implemented as follows:

- **Place-based interventions** reduce locational suitability in the target grid cells (top 45 highest crime areas) by 50 percent. The intervention will occur once halfway through the model run. The 50 percent reduction is arbitrary and chose as an initial benchmark condition. Sensitivity analyses are used to test whether model outcomes are different if 25 percent and 75 percent reductions are assumed.

- **Person-based interventions** target offenders who have committed crimes in the target location in the previous year. The targeted individuals will be forced out of offender history lock-in at this location. This means that the probability of selecting the target location from their own offending history is set to 0.0 for the remainder of the simulation. The exact nature of the intervention is not considered here but suggestions are discussed in the next chapter. This experiment is only meant to observe what would happen to crime in a location if this type of treatment is used.

- **Network-based interventions** also target individuals who committed crimes in the target location in the previous year. These targeted individuals will be forced out of co-offender history lock-in at target locations. This means that the probability of selecting a targeted location from their co-offenders’ history is set to 0.0 for the remainder of the simulation. Again, the exact nature of the intervention is not considered here.
Place-based interventions are predicated on the idea that offenders select crime locations that are most suitable. It follows that reductions in place suitability should decrease crime at target hot spots. But positive feedbacks in offender decision making (e.g., status quo bias) make crime patterns resistant to such place-based changes.

Hypothesis 3: Crime control interventions that reduce locational suitability at crime hot spots will be less effective when status quo bias has stronger effects on crime location choice.

Hypothesis 4: Crime control interventions that disrupt offender history or co-offender history effects at crime hot spots will be more effective than place-based interventions when status quo bias has stronger effects on crime location choice.

Paired samples design. One advantage of agent-based modeling is the ability to have strict control over all components in the modeling environment. The ideal experiment in this context allows the researcher to hold all conditions constant, varying only the decision making rules to test the effects on outcomes. In practice, this is implemented by setting the pseudo-random number generator seed to be the same in each run across experimental conditions. In other words, suppose 100 model runs are simulated under two alternative conditions and average outcomes are compared between conditions. The seed is set to 12345 during run 1 in condition 1. The environment is cleared, and the seed is again set to 12345 during the first run in the second condition. This ensures identical starting states between paired runs, holding all things constant.
between conditions except the assumption of interest. Each experimental condition is treated as a unique and perfect counterfactual.

Past work tends to rely on thousands of model runs to rule out random variation that might otherwise explain differences between experimental conditions. One implication of using paired runs as in the present design is that thousands of model runs are not necessary. Fewer runs are necessary to make inferences. This is comparable to using a paired samples design without concerns over testing effects or sample maturation effects.

**Power analysis.** Given the paired samples design, power analysis was used to determine that 45 paired model runs are necessary to observe a medium-sized mean difference ($d_z = 0.5$) between two dependent (matched) groups (assuming $\alpha=0.05$ and $1-\beta=0.95$). Mean values in this context are computed for outcomes of interest across model runs within the same experimental condition. That is to say that 45 paired runs in an experiment (pairing two conditions) is sufficient to observe a mean difference between conditions that is at least half as large as the standard deviation of the differences (Cohen, 2013).

**Analysis**

For each experiment performed, the simulation model was run 45 times under each experimental condition and the average outcome over the runs is reported. Comparisons are made using analysis of variance (ANOVA) and paired samples $t$-tests to determine whether outcomes significantly differed across experimental conditions. Graphs will also be used to visualize differences in *annual* outcome values averaged over
all model runs, by experimental condition. The mean trend ± 2 standard errors will be shown to assess significant differences among experimental conditions over time. These graphs also assess stability in the outcome measures across time within each run.

**Results**

Table 5.3 summarizes results from the first experiment testing the effects of status quo bias on key outcome measures. The f-tests from one-way ANOVA suggest significant differences in spatial crime concentration and hotspot stability across experimental conditions by all measures examined. Table 5.4 provides pairwise t-tests to indicate specific differences. Crime patterns generated with history effects are significantly more concentrated and significantly more stable than when crime patterns are generated without history effects. The differences are larger for strong history effects than weak effects. Null history effects generate patterns that require 19.29 percent of areas to account for 50 percent of the crimes. This is reduced to 13.09 percent of areas for patterns generated by strong history effects, implying a 32 percent increase in concentration (difference = -6.20; SE = 0.09; \( t = -66.44 \); \( p < .001 \)). Regarding the percent of areas necessary to account for 25 percent of the distribution, strong history effects generate patterns that are 36 percent more concentrated (difference = -2.76; SE = 0.04; \( t = -64.76 \); \( p < .001 \)). Similarly, dispersion measured by the Gini coefficient is 25 percent higher from strong history effects than in the null effects condition (difference = 0.13; SE = 0.001; \( t = 71.88 \); \( p < .001 \)).
Table 5.3. Mean crime concentration and hot spot stability by experimental condition.

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Condition 1 Null History Effects</th>
<th>Condition 2 Weak History Effects</th>
<th>Condition 3 Strong History Effects</th>
<th>( F )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean (SD)</td>
<td>Mean (SD)</td>
<td>Mean (SD)</td>
<td></td>
</tr>
<tr>
<td><strong>Concentration</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>50% Hotspots</td>
<td>19.20 (0.28)</td>
<td>18.02 (0.28)</td>
<td>13.12 (0.51)</td>
<td>3346.23***</td>
</tr>
<tr>
<td>25% Hotspots</td>
<td>7.47 (0.13)</td>
<td>6.96 (0.13)</td>
<td>4.76 (0.25)</td>
<td>2790.69***</td>
</tr>
<tr>
<td>Gini Coefficient</td>
<td>0.52 (0.01)</td>
<td>0.55 (0.01)</td>
<td>0.65 (0.01)</td>
<td>3980.39***</td>
</tr>
<tr>
<td><strong>Stability</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Overlap of…</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>50% Hot Spots</td>
<td>38.48 (0.96)</td>
<td>41.47 (1.60)</td>
<td>54.13 (2.10)</td>
<td>1180.35***</td>
</tr>
<tr>
<td>25% Hot Spots</td>
<td>20.41 (1.36)</td>
<td>25.39 (1.91)</td>
<td>42.95 (3.64)</td>
<td>1008.73***</td>
</tr>
<tr>
<td>Coefficient of Variation</td>
<td>0.75 (0.01)</td>
<td>0.76 (0.01)</td>
<td>0.68 (0.02)</td>
<td>257.78***</td>
</tr>
</tbody>
</table>

**NOTES:** df=134.  
**ABBREVIATIONS:** SD=standard deviation.  
*** p<.001.

Figures 5.6 and 5.7 illustrate average outcomes over time by experimental conditions. The mean ± 2 standard errors for runs is displayed. Figure 5.6.1 shows the average percent of locations that account for 50 percent of the crime distribution. Lower values represent higher concentration. The strong history effects condition shows significantly higher concentration across time by all metrics, whereas the confidence interval for the weak history effects condition overlaps with the null history effects condition in later time periods. A similar result is shown in Figure 5.7 for hotspot stability. Hot spots generated by strong history effects are consistently more stable over time than when weak or null history effects are assumed.
Table 5.4. Paired sample *t* tests for crime concentration and hotspot stability.

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Difference (SE)</th>
<th>Lower</th>
<th>Upper</th>
<th><em>t</em></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Weak History Effects vs Null History Effects</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Concentration</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>50% Hotspots</td>
<td>-1.17 (0.05)</td>
<td>-1.27 -1.07</td>
<td>-23.10***</td>
<td></td>
</tr>
<tr>
<td>25% Hotspots</td>
<td>-0.51 (0.02)</td>
<td>-0.56 -0.46</td>
<td>-21.01***</td>
<td></td>
</tr>
<tr>
<td>Gini Coefficient</td>
<td>0.02 (0.001)</td>
<td>0.024</td>
<td>23.24***</td>
<td></td>
</tr>
<tr>
<td>Stability</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Overlap of...</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>50% Hot Spots</td>
<td>3.00 (0.26)</td>
<td>2.48 3.52</td>
<td>11.67***</td>
<td></td>
</tr>
<tr>
<td>25% Hot Spots</td>
<td>4.98 (0.36)</td>
<td>4.25 5.71</td>
<td>13.75***</td>
<td></td>
</tr>
<tr>
<td>Coef. of Variation</td>
<td>0.01 (0.003)</td>
<td>0.02</td>
<td>4.34***</td>
<td></td>
</tr>
<tr>
<td><strong>Strong History Effects vs Null History Effects</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Concentration</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>50% Hotspots</td>
<td>-6.07 (0.08)</td>
<td>-6.23 -5.91</td>
<td>-76.54***</td>
<td></td>
</tr>
<tr>
<td>25% Hotspots</td>
<td>-2.71 (0.04)</td>
<td>-2.79 -2.63</td>
<td>-68.58***</td>
<td></td>
</tr>
<tr>
<td>Gini Coefficient</td>
<td>0.13 (0.001)</td>
<td>0.12 0.13</td>
<td>86.94***</td>
<td></td>
</tr>
<tr>
<td>Stability</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Overlap of...</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>50% Hot Spots</td>
<td>15.66 (0.40)</td>
<td>14.86 16.45</td>
<td>39.64***</td>
<td></td>
</tr>
<tr>
<td>25% Hot Spots</td>
<td>22.54 (0.61)</td>
<td>21.31 23.76</td>
<td>37.20***</td>
<td></td>
</tr>
<tr>
<td>Coef. of Variation</td>
<td>-0.07 (0.004)</td>
<td>-0.07 -0.06</td>
<td>-16.90***</td>
<td></td>
</tr>
</tbody>
</table>

**NOTES:** df=44. *** p<.001.

**ABBREVIATIONS:** SE=standard error of the difference.
Figure 5.6. Crime concentration outcomes over time, by experimental condition, showing mean and ± 2 standard deviations over 45 runs.
Table 5.5 shows results from experiment 2 testing the effects of different types of interventions aiming to reduce crime at target hotspot locations. There are significant differences in the mean number of crimes that occur in target locations between preintervention and postintervention periods across the four experimental conditions ($f=345.21$; $p<.001$). There are also significant differences in the standardized pre-post
difference as measured by the t-score ($t=308.49$; $p<.001$). Conditions 4 and 5 represent cases when a place-based intervention is implemented that reduces locational suitability by 50 percent in 45 target hotspots. When history effects are absent (condition 4), the average crime change between preintervention and postintervention periods is a significant reduction of 8.09 crimes across model runs (SD=1.03; mean $t=–6.49$; SD $t=0.84$). When history effects are present (condition 5), there is an average reduction of only 1.26 crimes (SD=1.17), and it is nonsignificant on average across model runs (mean $t=–1.21$; SD $t=1.06$). This demonstrates the resilience of hotspots to place-based interventions when status quo biases (history effects) are present in crime location choice.

**Table 5.5.** Intervention effects on crime counts in target hotspots across 45 model runs, by experimental condition.

<table>
<thead>
<tr>
<th>Cond.</th>
<th>History Effects</th>
<th>Intervention Type</th>
<th>Crime Count Change in Target Hotspots Mean (SD)</th>
<th>$t$-value for Crime Count Change Mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>Null</td>
<td>Person-based</td>
<td>– 8.09* (1.03)</td>
<td>– 6.49 (0.84)</td>
</tr>
<tr>
<td>5</td>
<td>Strong</td>
<td>Person-based</td>
<td>– 1.26 (1.17)</td>
<td>– 1.21 (1.06)</td>
</tr>
<tr>
<td>6</td>
<td>Strong</td>
<td>Person-based</td>
<td>– 4.45* (1.27)</td>
<td>– 3.48 (0.71)</td>
</tr>
<tr>
<td>7</td>
<td>Strong</td>
<td>Person-based</td>
<td>– 11.28* (2.41)</td>
<td>– 4.95 (0.77)</td>
</tr>
</tbody>
</table>

$F = 345.21^*$ $F = 308.49^*$

**NOTES:** $df = 179$. $^* p<.001$.

**ABBREVIATIONS:** SD=standard deviation.
Experimental conditions 6 and 7 implement person-based and network-based interventions to target crime hotspots by disrupting decision making links with history. Person-based interventions are implemented by removing target locations from an offender’s crime location history. Network-based interventions remove target locations from co-offender crime histories. The results show that person-based interventions significantly decrease crimes at target locations by 4.45 events on average (SD=1.27; mean $t=-3.48$; SD $t=0.71$), and network-based interventions significantly decrease crimes at target hotspots by 11.28 events on average (SD=2.41; mean $t=-4.95$; SD $t=0.77$). This demonstrates the potential crime reduction effects of person-based and network-based interventions when status quo biases are able to override place-based strategies.

**Discussion**

Details in the microscopic decision making of offenders have important implications for macroscopic patterns of crime. This dissertation argues that status quo bias in crime location choice is sufficient to generate geographic crime patterns that are highly concentrated, temporally stable, and resistant to location changes. Rigorous experimentation on an agent-based model provided evidence that the hypothesized mechanisms produce signature characteristics of crime. In short, status quo biases make crime concentrate in stable hotspots year after year. Further, place-based interventions that would be effective at reducing crime in the absence of status quo bias were found to exert null effects when history effects were present. Alternatively, adopting interventions
that specifically disrupt status quo biases were shown to have crime reduction effects at
target locations as intended.

These results have implications for crime theory and policy. Status quo biases in
offender decision making do not only affect individual crime events. The aggregate
consequences of crime location re-selection include high clustering of crime and stability
of crime hotspots over time, above and beyond the role of place characteristics. The
micro-macro relationship between individual decisions and aggregate crime patterns is
not simple aggregation of independent events. Crimes are historically dependent on one
another. Just like the urn models described in Chapter 3, this means that one crime event
could theoretically initiate a growing crime problem if offenders choose to re-select the
same location repeatedly. This could explain why certain high crime places are
persistently risky over time (Andresen et al., 2017; Andresen & Malleson, 2011; Braga et
al., 2010; Papachristos, 2013; Sampson, 2012; Shaw & McKay, 1942; Vandeviver &
Steenbeek, 2019; Weisburd et al., 2004), yet the explanation has little to do with the
conditions of those places.

This type of positive feedback process has been discussed in the crime and place
literature (Bursik Jr, 1988; Skogan, 1992; Taylor, 2015; Wilson & Kelling, 1982), but
never before has it been conceptualized as a result of individual-level decision making.
Prior research attributes positive feedbacks to location, but the current research suggests
that it could also stem from mechanisms in microscopic decision making. To wit, status
quo bias in crime location choice is a sufficient explanation for positive feedbacks in
geographic crime patterns. The agent-based model results support this conclusion, as
crimes were more highly concentrated in hotspots that were more stable over time as a
result of status quo biases. It is possible that more long-term feedbacks would also result, compounding the problem through place-based causal pathways as well. But direct history effects are sufficient to generate this pattern. This is important because it offers an alternative point of intervention at the micro level. As I discussed in Chapter 3, targeting crime problems at the individual level offers a more direct disruption of positive feedback loops, whereas place-based interventions are more indirect, can require extensive resources, and often take longer to observe effects.

Moreover, the above experiments demonstrate that place-based interventions may not achieve desired crime reductions when history effects are present. The current research raises substantiated concerns about widespread adoption of place-based strategies without considerable reserve about the potential limits of their effectiveness. The previous chapter showed evidence of the hypothesized history effects (status quo bias), net of a robust set of controls. This could explain why place-based interventions do not always generate large crime reductions (Braga et al., 2014; Collazos et al., 2020; Hunt et al., 2014). This is combined with concerns about the potential negative consequences for procedural justice and increased inequalities associated with place-based interventions (Harcourt, 2009; Rosenbaum, 2006). This is not to say that place-based programming is ineffective or doomed to diminish social justice. In fact, place-based interventions can reduce crime, as exemplified by programs such as hotspots policing (Braga et al., 2014) or the removal of urban blight in vacant areas (Branas et al., 2018). Furthermore, data-driven strategies such as predictive policing have been shown to not increase racial inequalities (Brantingham et al., 2018) and additional practices have been proposed to limit inequalities (Wheeler, 2019). While this is promising, this study
points towards alternative strategies which can be used to directly address historical feedbacks with greater control over who is being targeted by the intervention.

**Limitations.** The most notable limitation of agent-based models is the use of an artificial environment to make inferences about social processes. Many model parameters were derived from empirical sources, but the ‘data’ are nonetheless created from computer simulation. Birks et al. (2012) note that agent-based models are limited by the imagination of the researcher, their technical ability, and computational resources available to them. Some people may have great reservations about trusting findings from the imagined world of a researcher, but the ability to replicate the model allows knowledge to build incrementally and test alternative explanations. This dissertation challenges future research to improve upon current modeling specifications to align simulation processes more closely with reality. In the present context,

One position is that the advantage of rigorous theory testing without having to conduct expensive or unethical experiments in the real world outweighs the disadvantages of using simulated data. As Birks et al. (2012) note, “the generative [agent-based model] may provide an ethically, logistically, and monetarily inexpensive method for rapidly prototyping theoretical propositions” (p. 243). Path dependence theory is in its infancy in criminology, so the advantages of further pursuing its propositions using simulation may outweigh the disadvantages.

Secondly, there are several instances where parameter values were arbitrary chosen without estimates from empirical data. The number of offenders that were present in the model at any given time, for instance, was arbitrary. During model testing and design, it was found that allowing fewer offenders in the model created data sparseness
concerns. This may be important for developing models of rare crimes, such as homicide, because model outcomes may be more chaotic with fewer crimes. This problem parallels the general issue of statistical power and is not necessarily specific to agent-based modeling.

Third, the agent-based model, like all models, is a simplified representation of reality. Many processes that occur in the real world are ignored. For instance, all offenders in the model have the potential to commit crimes between the ages of 12 and 69, which ignores the possibility that some offenders die earlier or are incapacitated (e.g., arrest, incarceration) which would eliminate them from the potential offending pool. Future research should consider how these types of important criminological processes might affect spatial crime patterns. Note, however, that these processes are held constant across all experimental conditions and should not affect outcome comparisons described herein.

Fourth, agent-based models are used to test whether hypothesized mechanisms are “generatively sufficient” to produce outcomes of interest (Epstein, 1999). This means that the processes modeled in the simulation are sufficient to generate common crime patterns (Birks et al., 2012). This also means that agent-based models cannot rule-out alternative explanations that are not implemented simulation.

Finally, the second experiment tested how different types of interventions affected crime at hotspot locations but did not specify how those interventions would be implemented in practice. In particular, it is somewhat unclear how the police or other organization might intervene to disrupt status quo biases that have been established by previous crimes. This ambiguity was somewhat intentional to allow a range of
possibilities that should be explored in future research. The next chapter offers some promising options in hopes of inspiring more work on the general idea.

**Conclusion**

This chapter described the construction, implementation, and analysis of an agent-based model used to test key hypotheses derived from path dependence theory. The results show that status quo biases in microscopic decision making have significant effects on aggregate crime patterns. The hypothesized history effects generate positive feedback, causing crimes to concentrate in stable hotspots over time. This indicates that chronic crime problems may stem from an individual or group-level process that has little to do with places themselves. The results show that large-scale place changes may not even reduce crime in hotspot areas when path dependence is at play. This implies critical limits to place-based crime reduction strategies and offers new alternative pathways for reducing crime through individual and network-based mechanisms. The model did not detail how those alternative interventions might be implemented in practice, but the next chapter offers some possibilities in light of the experiment results.
Chapter V. Implications and Conclusions

The goal of this dissertation was to propose a new idea about how individuals decide where to commit criminal offenses to explain why crimes cluster and generate chronic crime hotspots. Simple rules about microscopic decision making were described that have complex consequences for macroscopic crime patterns. The presence of these processes has important implications for how we think about crime, study geographic crime patterns, and develop effective crime reduction initiatives. This chapter outlines these in greater detail to justify the importance of this research.

Theoretical Implications

Path dependence theory has forced theorists in other fields of social science to rethink the processes underlying patterns of behavior. Criminologists are similarly challenged to consider the role of positive feedback loops in issues of crime and justice. The current study contributes to these discussions by recognizing the importance of processes operating at different scales of analysis. In particular, I argue that aggregate patterns of crime, including crime at micro-places, is driven largely by the microscopic decision making of potential offenders. In so doing, this research directly addresses link 3 in micro-macro causal structures that is often an Achilles’ heel of social theory (Coleman, 1990; Hedström, 2005; Hedström & Swedberg, 1998; Matsueda, 2017; Short Jr, 1985, 1998; Taylor, 2015). The theoretical ramification of path dependence is that crime location choices are endogenous and can eventually lock-in to a stable pattern. Being locked-in makes crime problems highly resistant to change unless the positive feedbacks can be disrupted.
It is also important to note that the micro-macro relationship is nonlinear. The link between place characteristics and aggregate crime patterns (link 4 in figures above) is complex and not deducible to independent decisions made at a micro-level. This means that outcomes are more unpredictable than if the micro-macro link were simple aggregation (Coleman, 1990; McGloin et al., 2011), and allows chance to influence actual crime patterns (Arthur, 1990a). More work is needed to determine the conditions under which chance has greatest impacts and how policy might leverage the role of chance processes to reduce harm in communities.

I further argue that current models of offender decision making logically explain how rational individuals should select crime locations, but that the model should be modified to better describe how these processes actually occur. This approach is based on a robust line of research in behavioral economics finding that people tend to behave in ways that conflict with the neoclassical rational utility model (Kahneman et al., 1991; Tversky & Kahneman, 1974). As Thaler (2015) suggests, people tend to “misbehave” in relation to the assumed model. Many criminological theories make similar assumptions about decision making that can be updated with contemporary understanding from other fields, as was suggested here. This builds on an existing body of criminological research examining decision making processes (Pogarsky et al., 2018), and opens the door to additional unanswered questions about the microscopic origins of macro-level patterns.

In some ways, path dependence can be seen as a rejection of mainstream theory. I argue that place conditions may not be wholly responsible for the crimes that occur (or do not occur) there. Parallel propositions have been made in other scientific fields, including institutional sociology (David, 1994), economics (Arthur, 1988b), politics (Pierson,
The argument is commonly met with skepticism and strong reservations, given the inherent pushback on conventional theory. Perhaps this represents a pattern of path dependence in academia, whereby status quo theories are preserved in spite of more efficient alternatives. Large investments have been made into theories and mechanisms are in place to resist change and uphold the status quo. It follows that the field may be locked-in to a given set of theories and will require substantial effort to consider their limitations seriously. More studies are needed to examine path dependence theory, including its strengths and weaknesses in relation to crime.

Yet, the present research did not entirely invalidate existing theories of crime. In fact, micro-level decision making analysis showed that many place characteristics were predictive of crime location choice, net of history effects. Relatedly, the agent-based model included key components from crime theories, such as the role of routine activities and awareness spaces, in crime location selection. Both place and history influence offender decision making and the resulting geographic crime patterns. A key takeaway, however, is that individuals consider more than just locational suitability when selecting crime sites, implying a relaxation of the crime suitability assumption. History is one additional consideration that should become more prominent in criminological inquiry.

**Methodological Implications**

The present research is another example of how computational modeling can be a powerful form of scientific inquiry (Birks et al., 2012; Brantingham, 2011; Brantingham & Brantingham, 2004; Epstein, 1999; Groff, 2007; Groff & Birks, 2008; Groff et al.,
As noted above, this approach offers a means for investigating rigorous counterfactuals that are impossible to examine in the real world. It is not possible, for instance, to observe the macro-level consequences of alternative decision making processes using real offenders. In other contexts, it may be possible but unethical to create the necessary counterfactuals. While real world experimentation and observation will always be essential, computational models can serve as useful tools to help us think about our theories and their implications (Edmonds & Hales, 2005). In some instances, especially when little is known about a process, simulation is a relatively cheap way to explore new possibilities and examine the potential limits of different types of policies. This study shows these advantages by exploring the implications of path dependence theory in relation to alternative interventions designed to reduce crime. While simulation should not be the only evidence driving crime policy, it does serve a critical purpose in that process.

Another consideration implied by this research is the idea that individuals are not always aware the factors underlying their behavior. Here I found that offenders may be subject to status quo biases, which is at odds with qualitative research suggesting that offenders regularly use calculated decision making and environmental cues when committing crimes (Rengert & Wasilchick, 1985; Rossmo & Summers, 2019; St. Jean, 2008; Wright & Decker, 1996, 1997). This could mean that asking offenders directly about how they make decisions may not always align with how they actually make decisions in the moment. This would not be unusual, given that people are often unaware of their biases (Samuelson & Zeckhauser, 1988), and it raises concerns about the utility of relying on offender accounts exclusively for developing policies designed to influence
their decisions. More work should be done to identify the contexts in which biases are most influential and when calculated decisions are more likely at play.

Policy Implications

The path dependence argument is important because it describes an alternative process that has been largely ignored in discussions of crime and place. But if path dependence matters very little and locational suitability is the dominant process, then identifying, measuring, and changing the place conditions that contribute to suitability is worth the effort. Let us assume for a moment that mechanisms of path dependence play an important role in crime and consider what implications this has for criminal justice policy and practice. The following discussion will address two primary considerations including (1) disrupting the growth and sustainment of crime problems and (2) the potential limits and minimum necessary effects of place-based interventions.

Path dependence processes generate positive feedback, causing crime problems to grow at an increasing rate. Once a certain point is reached, crime problems can become locked-in and difficult to reverse. Disrupting the growth and sustainment of crime requires interventions that address positive feedback mechanisms. One such mechanism involves status quo biases that refer to the habituation of crime location choices by offenders and co-offending groups. When multiple crimes occur in the same place, it becomes increasingly likely that more crime will follow because offenders will repeat their own behaviors and imitate their associates. Small crime problems can become larger at an increasing rate, an argument that parallels the broken windows thesis (Wilson &
Kelling, 1982). Small crime problems should not be ignored lest they become more serious and difficult to reverse.

Although path dependence appears to parallel the broken windows argument, the policy implications of these two theories diverge in important ways. The broken windows thesis has received a great deal of negative attention in the literature. Disorder is argued to be a subjective phenomenon that is socially created and tends to be conflated with race (Harcourt, 2009; Sampson & Raudenbush, 2004). Further, broken windows policing tactics such as stop-and-frisk have been criticized for producing racial disparities, rather than reflecting them (Goel et al., 2016). The key implication of broken windows is that it is a place-based process: disorder in a place has a criminogenic effect that attracts offenders who perceive that crime is accepted in that place (Wilson & Kelling, 1982). While some evidence for this proposition exists (Keizer et al., 2008; St. Jean, 2008), less evidence demonstrates that the process works in reverse – that decreasing “disorder” (however defined) will decrease an existing crime problem (but see, Moyer et al., 2019). According to the path dependence argument, the place conditions that might initiate a sequence of crimes may have little to do with causing it to grow at an increasing rate and may not be useful in decreasing the problem once it has become locked-in.

Targeting areas with increased policing and enforcement, rather than targeting known offenders, can be risky from a social justice standpoint. While increased police presence is believed to achieve a place-level crime reduction effect (Braga & Weisburd, 2010; National Academies of Sciences & Medicine, 2018), it can also have negative consequences. Cooper et al. (2005), for example, found that police crackdowns made it
more difficult for drug users to engage in harm reduction behaviors.\textsuperscript{19} Moreover, increased police presence to address disorder problems is likely to result in more arrests for low-level crimes, which has a negative impact on perceptions of procedural justice and police legitimacy (Gau & Brunson, 2010). In particular, disadvantaged areas are most at risk for negative consequences of low legitimacy (Kane, 2005). When residents experience negative encounters with police, they become cynical and less likely to call the police (Carr et al., 2007), which can decrease access to critical harm-reduction resources such as victim services or medical care. On the other hand, positive police interactions can have a positive effect on perceptions of legitimacy (Mazerolle et al., 2013) which implies that targeting problem areas appropriately could have the intended deterrent effects without negative repercussions.

Place-based approaches to crime problems are predicated on the notion that a few places account for the bulk of crime (Braga & Weisburd, 2010; Eck & Weisburd, 1995; Weisburd et al., 2016). Nonetheless, we can similarly assume that most people in any given space do not engage in criminal behavior, implying that a few prolific offenders are responsible for most criminal activity (Bouchard & Konarski, 2013; Clarke & Eck, 2016; Martinez et al., 2017; Natarajan, 2006; Spelman & Eck, 1989). It follows that alternative strategies might include person-based or network-based interventions that combine the principles of focused deterrence (Kennedy, 2012).

Not only are the highest rate offenders also more likely to commit crimes in the same places to reinforce status quo behavior, but others in their co-offending network are

\textsuperscript{19} The authors describe how frequent body searches discouraged participants from carrying sterile drug injection equipment. Additionally, homeless women and men found it difficult to inject safely when police were continuously monitoring public spaces.
also more likely to commit crimes there. Overcoming offenders’ perceptions that a given area is ‘good’ for crime may therefore involve targeting the highest rate offenders in the area, rather than targeting the entire area which could result in wasted energy and social justice violations. Focused deterrence programs have generally shown crime reduction effects, particularly in instances where they are designed to address conflicts among criminal groups (Braga et al., 2018). Path dependence is another theoretical argument to justify the use of these types of programs. Even if the goal is to reduce the crime problem in a specific geographic area, focusing on the people responsible rather than the place itself could be a more efficient path to crime reduction (Ratcliffe, 2003) with fewer risks to social justice.

Path dependence also suggests the ways in which interventions can improve efficiency. Intelligence-led policing is becoming a popular framework for decision making in law enforcement. One form of police intelligence that is increasingly useful involves social network analysis to understand connections between individuals, events, and places (Bichler et al., 2017; Papachristos & Sierra-Arevalo, 2018). One claim of path dependence suggests that crime clusters and spreads through social network relationships. This implies that we can identify offenders that are most “central” to the crime network, and that removing them from the network could have a large effect on the diffusion of crime. One common family of metrics in social network analysis is that of centrality, which refers to measures that describe how a particular node (e.g., individual) contributes to the structure of the network (Borgatti et al., 2018). In particular, betweenness centrality identifies nodes within the network that are in a “position to threaten the network with disruption of operations” (Borgatti et al., 2018, p. 201). Police could potentially achieve
more efficient crime reductions by employing social network analysis to identify not only the most frequent offenders, but also those that are most central to crime networks that, if removed, could cause substantial disruptions to the diffusion of crime (Bright et al., 2014; Bright et al., 2015; Morselli & Petit, 2007; Zhang, 2014). Targeting these “central” individuals, either for deterrence purposes or even to use them as key informants, could prove even more useful than currently assumed if path dependence is at play.

While path dependence implies that person-based or network-based interventions are likely to disrupt crime problems, place-based interventions are at odds with the argument. In its purest form, path dependence implies that location characteristics exert neutral influence on the likelihood of crime (i.e., history matters, not place). Changing place characteristics would have no effect on crime if path dependence was the only process at play. But observed patterns are more likely to reflect the combined influence of path dependence and locational suitability. The relative influence of these processes implies the degree to which interventions which address their respective mechanisms will potentially be effective. Suppose that path dependence and locational suitability are equally responsible for generating crime patterns. An intervention designed only to change the characteristics of a given place to reduce its crime problem (e.g., reduce disorder, increase willingness of residents to intervene, increase police presence) can only be expected to contribute a 50 percent decrease in crime on average, if it makes the area unsuitable for crime. If the path dependence-suitability split is 80-20, the effects of place-based interventions should be expectedly lower. In the current study, a 2-to-1 split (empirically justified by results presented in Chapter 4) was sufficient for history to overrule large reductions in place suitability.
One purpose of understanding the role of path dependence is that it allows us to identify an upper limit on interventions that do not address the ways in which positive feedbacks drive crime. On the other hand, it also could provide a minimal level of change that would be required by place-based approaches to achieve intended effects. In other words, it could be the case that location changes must reach a certain threshold to overcome positive feedback effects. Dramatic changes in a place may result in crime reductions (or unfortunately, increases), but small changes may not be enough. Many scholars have argued that programs and policies aiming to improve conditions in disadvantaged, high crime places must be wide in scope and sustained over time if they are to be expected to achieve intended effects (Sampson, 2012; Sharkey, 2013; Wilson, 1987). In the same way that we conduct power analyses to determine required sample sizes to observe effects (Cohen, 2013), we might similarly determine how much place-based change would be necessary to override positive feedback processes; programs or policies that do not expect large enough effects can be abandoned or improved to sufficient levels. Such knowledge may be achievable if greater scientific attention is paid to counterfactual processes such as path dependence.

**Conclusion**

This chapter outlined some of the major implications of the research presented herein. I argue that status quo bias is one potential mechanism of path dependence that causes geographic crime patterns to be highly concentrated and stable over time. I further suggest that crime policies should consider these history effects when developing crime reduction initiatives. While path dependence is only one of many processes underlying
crime patterns, its influence can be substantial and may outweigh the effects of other processes in certain contexts. Much is to be learned about these processes and the best ways to improve conditions in places that experience a large amount of crime. I argue that the key is to first recognize the place of historical path dependence in geographic criminology.
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