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# Geographic space and time:
# The consequences of the spatial footprint for neighborhood crime

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Criminology, Law and Society

by

Adam Boessen

Dissertation Committee:
Professor John R. Hipp, Chair
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2014

*Dedicated to my family and friends. Thank you for all you do!*

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## Acknowledgements

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- Hipp, J. R., C. T. Butts, R. M. Acton, N. N. Nagle, and **A. Boessen**. (2013). Extrapolative simulation of neighborhood networks based on population spatial distribution: Do they predict crime? *Social Networks.* 35: 614-625.
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# Abstract of the Dissertation


Geographic space and time:
The consequences of the spatial footprint for neighborhood crime

By

Adam Boessen

Doctor of Philosophy in Criminology, Law and Society

University of California, Irvine, 2014

Professor John R. Hipp, Chair



Many disciplines frequently use residents' home neighborhoods as a proxy for their entire social lives, which ignores people's temporary spatial presence in other neighborhoods for activities such as work and school. While most research only uses information on where people sleep - their home residence, my dissertation investigates this gap in the literature by focusing on the daytime movements of residents and how different areas of the city are interrelated over the day. My dissertation examines the spatial travel patterns of people over time - what I refer to as the *spatial footprint* - and uses these *spatial footprints* to understand local crime patterns in 13 cities over the day, week, and season. By focusing on the distinct spaces of individuals' daily activities and their relevant social space over the day, I dynamically model the changing activity and availability for social control across time, examine issues that are often treated as statistical nuisances (e.g., selection effects) as theoretical processes, and explicitly investigate how the nearby area and the interdependencies between neighborhoods matter for crime. I also examine crime within and around different land uses, including residential, commercial, school, and industrial areas, as they are occupied (or unoccupied) throughout the day, week, and season.

# Chapter 1

# Dissertation Introduction

Cities are dynamic and different parts of the city buzz with activity as the day unfolds. For instance, many retail spaces are lively during the day and early evening, while offices and businesses in downtown areas sit vacant during the nighttime. Neighborhoods with schools are active during the week, particularly in the mornings and afternoons, but are often unoccupied on weekends, evenings, and during the summer. These patterns suggest that people are located in different spaces of the city at different times of day.

Many disciplines frequently use residents' home neighborhoods as a proxy for their entire social lives, which ignores people's temporary spatial presence in other neighborhoods for activities such as work and school. Rather than a strategy that only uses information on where people sleep - their home residence - my dissertation is informed by a variety of fields and focuses on the daily, weekly, and seasonal spatial travel patterns of people - what I refer to as their *spatial footprint*. In my dissertation, I examine the consequences of these movement patterns for individual and neighborhood processes. My dissertation bridges work on defining neighborhoods, the spatial and temporal aspects of everyday activities, and land uses to focus on micro patterns of crime over time, neighborhood change, and daily activities.

My dissertation is guided by one simple insight: people move around and are not located in only one space over time. Much of the social science literature and theory approaches social phenomena as essentially static, existing, and with actors already in position. While some work will examine broad patterns of change over longer-periods of time (e.g., over decades or years), we have little understanding of change in everyday life. Most often the mechanisms and motivations (e.g., social control, social influence, inequality, etc.) are not spatially or temporally specific and are often treated as being applicable in all spaces and times. In what follows, I argue that spatial footprint patterns are one approach for situating and positioning social processes (e.g., various motivations and mechanisms) in space and time.

The first chapter of my dissertation theoretically situates the spatial footprint in a variety of literatures. Much of the spatial footprint research to date centers on an individual decision maker, and little emphasis is given to spatial and temporal processes associated with spatial footprint patterns. One distinction this dissertation makes from prior research is its focus on the *population* of different spatial footprint patterns, rather than individual footprint patterns. This leads to a discussion of how spatial footprints may impact the measurement of neighborhoods, the area nearby neighborhoods, and neighborhood crime.

Using the spatial footprint as an approach for understanding neighborhood processes, the next three chapters are motivated by three research questions:

1. Where are residents' spatial footprints?
2. What are the consequences of spatial footprints for perceptions of neighborhood processes?
3. What are the consequences for crime when people enter and exit neighborhoods over the day, week, and season?

The first research question is addressed in the third chapter of my dissertation. Using the Los Angeles Family and Neighborhood Survey (L.A.FANS), I use discrete choice models to explore how social distance, geographic distance, the distribution opportunities, and land use impact where residents go for a variety of activities, such as work, school, and grocery shopping. Rather than selection into neighborhoods as a statistical nuisance, this chapter examines activity location choice as a theoretical process. The results suggest that the vast majority of spatial footprint patterns are explained with physical distance.

In the fourth chapter, I again use the LAFANS data, and I examine how physical distance to a variety of activities has an impact on collective efficacy. While research on collective efficacy has renewed interested in neighborhood research, we have little work on the factors that influence collective efficacy. I find that the further residents' travel for amenities such as church and the grocery store, the less they perceive their neighborhood as collectively efficacious. The chapter concludes by focusing on how people's spatial footprints explicitly allows neighborhood researchers to put collective efficacy and other neighborhood processes into action.

While criminological research has focused on offenders' journeys to crime, the final empirical chapter focuses on how guardianship, the agents of social control, changes over micro spaces during different times of day when residents are at home, work, or school, and the consequences of these processes for crime. Using data from 13 cities across the US, I dynamically model the changing situational activity of the city across time by focusing on the distinct footprints of people's daily activities. Drawing from my interests in land uses, I also examine how crime patterns shift over different land uses, such as residential, commercial, school, and industrial areas, as they are occupied (or unoccupied) throughout the day, week, and season. The results suggest that many neighborhood effects are enduring suggesting a process akin to social disorganization theory, while other effects have considerable change suggesting situational routine activities' factors.

The dissertation closes with a discussion of the overall findings, general contributions to field and policy, and implications for future work on spatial footprints and crime. The spatial footprint may be of interest to fields beyond criminology for capturing movement patterns over the day.

# Chapter 2

# Contextualizing Spatial footprints and Crime

## 2.1 Introduction

People are located in a variety of contexts over time. A number of different fields have an interest in the spatial location of people over time, including geography, ecology, urban planning, sociology, psychology, criminology, physics, public health, biology, and computer science. With the use of pagers, cell phones, GPS, time use surveys, sensors, and other location-based systems, there is an increasing interdisciplinary interest in understanding an individual's spatial temporal movement patterns. These movement patterns can broadly be conceptualized as *spatial footprints*. There are a variety of definitions from different fields that all conceptualize and term something akin to a spatial footprint, and these include: individual paths (over a lifetime or a day) [76], potential path space and daily potential path area [155], journey or trip to various activities such as crime [185], action spaces and individual activity spaces [91], carbon footprint [221], and geospatial lifelines [139]. All of these approaches can be broadly conceptualized as a spatial footprint. For my dissertation, a spatial footprint is defined as an individual's movement pattern over time. It represents at least three domains: the journey between different locations, an individual's experience within a particular location, and the history of locations traveled. The implicit idea is where people go and when they are there.

As individuals travel to different locations, they will experience a variety of different contexts over time. This suggests two fundamental and intertwined issues: spatial uncertainty and temporal uncertainty [125, p. 959].[1] As suggested by Kwan, *spatial*

[1] These two issues were recently termed in the geography literature as the *uncertain geographic context*

*uncertainty* is the challenge of inferring the context that matters for someone's behavior. The question is: what context matters if people's locations are not static? Is it the home? The school? Work? Some combination of different locations? A focus on more than one location also necessarily implies *temporal uncertainty*: the timing and duration of different locations. Does the dosage of exposure to some context matter? Does a prior context matter for the current context? The uncertainty of space and time for individuals necessarily complicates exposure, embeddedness, social isolation, and influence conceptualizations for how context might matter for individual behavior [57].

Research on spatial footprints to date has almost exclusively focused on individual activity patterns, and how these patterns are important for a range of individual outcomes: access to food [108], access to health care [204], youth travel [227], mental health [47, 225], exposure to alcohol outlets [7], exposure to environmental pollutions, shopping, journey to work, and individual segregation [164]. The main conclusion from this body of knowledge is that individuals experience a variety of contexts over time. One commonality to this literature is its focus on individual units of analysis and how independent individual people make decisions. The spatial footprint of one person is implicitly a unique fingerprint for their experience in the social world. While appropriate for some research questions, it is unclear how individual spatial footprint patterns of everyday life relate to different neighborhood and contextual processes. Research on spatial footprints to date almost exclusively conceptualizes people operating independently. Each individual person is assumed to be on his or her own trajectory in space and time. My dissertation takes the next step in this research by examining how individual spatial footprints have consequences for aggregate group processes such as neighborhoods. The interdependence between people's spatial footprints gives insight for linking together micro and macro processes.

The neighborhoods literature routinely conceptualizes and measures the neighborhood context as a static administrative unit that impacts individual behavior. People are

*problem* (UGCoP) [124, 125] and as the issue of spatial polygamy and contextual exposures (SPACEs) [140].

bracketed, packaged, and neatly bounded into one contextual unit. These contextual units (i.e., "level two" units in multilevel terminology) essentially capture the total effect of context for individual behavior. One review from the neighborhood health literature found that 90% of studies only focus on one context - the home - and 73% use administratively defined units [131]. While appropriate for some research questions, this conceptualization is at odds with research showing that people experience at variety of contexts in everyday life. Most research only captures one state of the neighborhood within space and time. Much of the neighborhoods literature implicitly only focuses on when people are in and around their homes during the nighttime hours. This suggests two questions: 1.) Is the nighttime the appropriate time point to capture (temporal)? and 2.) Are people only exposed to one neighborhood context such as the home (spatial)?

With these questions in mind, I focus on three challenges for the spatial footprint literature that I refer to as *interdependence, temporal processes*, and *spatial processes*:

1.) Interdependence: Due in part to data limitations, the research on spatial footprints to date almost exclusively conceptualizes people operating independently. I take a different approach here. Spatial footprint patterns are jointly correlated and interdependent. The focus is not on individual behavior, but on different spaces over different time scales. As one example, a classroom is a meeting space for a teacher and students during the day, and this pattern suggests interlinked movement patterns. My approach focuses on people's joint distributions over different spaces of cities over time and the rhythm of mobility patterns in different spaces, rather than individual selection patterns of where they travel. This interdependence may help to situate many contextual processes and the interrelation between different areas of the city.

2.) Temporal Processes: We have little understanding the temporal scale of different individual and neighborhood processes, how different processes unfold over time, and the sequencing of different processes [2, 48]. Much neighborhood and spatial footprint research is ahistorical and emergent. My approach is interested in daily life that is ongoing and unfolding around different activities. With people traveling to different spaces, the explanation (i.e. the "causes") for crime and other social phenomenon may not be exclusively within one discrete concurrent context.

3.) Spatial Processes: The urban form, spatial scale, distribution of different activities, land uses and built environment necessarily constrain and attract various concentrations of different activities and the potential for different social processes. Most social science research outside of geography does not incorporate space as a factor for social processes, but as I discuss later, the space might be a particularly salient factor.

The purpose of this dissertation is to approach neighborhood processes with an explicit focus on the spatial temporal mobility patterns of people in their everyday lives and the consequences of these patterns for neighborhood crime. My focus here is on short-term (daily, weekly, seasonal) movement patterns of people. Other approaches and in fact the vast majority of research uses cross-sectional approaches or focuses on processes that occur over longer time scales, such as residential mobility patterns over decades and years. For example, changes due to residential migration capture *slower* broad patterns of neighborhood change, while daily or weekly travel patterns of commuting to various activities (e.g., work, school, etc.) are likely much *faster* [30]. While long-term patterns are interesting, my focus is on short-term processes.

In what follows, I review a variety of literatures that inform the spatial footprint approach, and the gaps and challenges with this literature. Next, I explicitly focus on criminological theory and the consequences of the spatial footprint for different crime patterns. Finally, the chapter closes with a brief discussion of spatial footprints and their application to my dissertation.

## 2.2 Situating the Spatial Footprint

### 2.2.1 Activity and Time Geography

Hägerstrand's (1970) *time geography* approach is the foundational work on spatial footprints, and it argues that space and time are fundamentally linked together [76] (see also [172]). While focused on individual behavior, he suggests that spatial footprints are theoretically constrained through three factors: capability (physiological needs), coupling (different activities in space and time), and authority (social and physical barriers) (see [64, p271]). His focus was on how capability, coupling and authority factors constrain the reach of people's activity patterns over the day and life course [64]. For example, research in this tradition would examine the extent of where people go for one entire day.[2] Incorporating Hägerstrand's ideas into a geographic information system (GIS), Miller (1991) examined the areas that an individual *potentially* could go given their constraints. Using not just the paths where people go, this approach incorporates the other potential paths or routes that someone could go to their destination [155].[3]

The time geography literature subsequently leads into the activity space approach that focuses again on individual activities (see [30, 64, 235] for a further discussion). Similar to the time geography approach, the activity approach is broadly interested in how individuals behave, make decisions about where they go, and how individuals use cities. Horton and Reynolds (1971) make a distinction between the spatial footprints of people's *communication* and *activity spaces* [91]. *Communication spaces* are the range of locations of people that someone communicates (e.g., using telephone) with over the day even though they are not physically present. *Activity spaces* are the set of *physical* locations that an

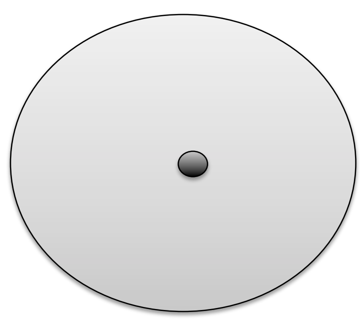
[2] Some of the early work systematically collecting data on youth movements was done by psychologists using paging devices to track how youth spend their time over the day. This research found that youth spend approximately a third of their time socializing with friends as well as a form of age based segregation [47]. Developmental psychologist Urie Bronfendrenner was also interested in the spatial footprint patterns of individuals. His work examined the multiple environments that people are constantly embedded throughout the life course [21, 22].

[3] One interesting insight from this approach is using network concepts to represent street networks (e.g. nodes as intersections, edges as streets).

individual actually travels over the day. For example, Farber (2013) examined the social interaction potential in and around work locations, rather than who people spoke with on the phone [60]. The majority of this literature has focused on various levels of accessibility via two factors: *constraints* on individual's movements or *attractions* to particular locations [156]. In this view, the spatial footprint can be considered a function of a variety of constraints on individual travel patterns in concert with the attractiveness of different entities.

There are several different approaches for measuring spatial footprints. Almost all measures start with people's home locations, which is reasonable given the amount of time and resources spent in/on this location. The inherent tension for this work is considering where people spend their time and how this relates to where they are currently located and their home. Although not clear what activities to include, most research uses one of the following measurement techniques:

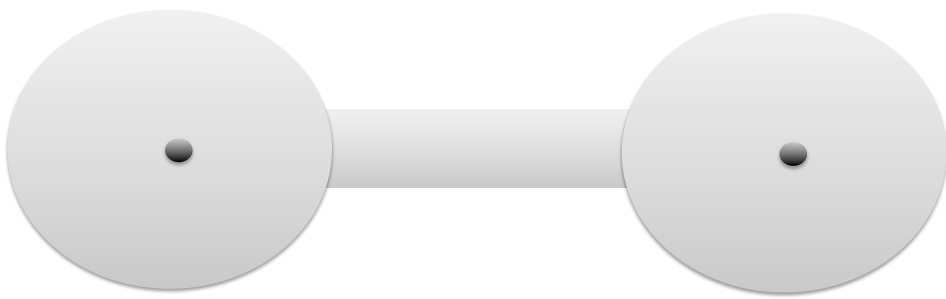
1. *Buffer around a point in space*: This approach takes a location (i.e., home, activity, start/end point, etc.) and draws a buffer of some size around the point. This approach results in a polygon(see Figure below), and this polygon is essentially the area of influence for this entity.



Note: The point would not be included in the polygon.

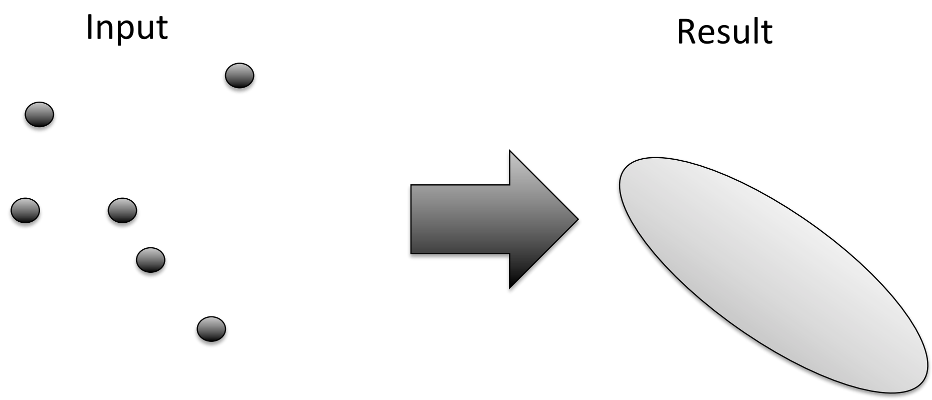
2. *Lines*: - This approach creates a line between two or more points (i.e., activity locations). The distance of the line is measured, and it represents the range of the footprint over space. For examples, see: [7].

3. *Buffer around paths to activities* - This approach is a hybrid between the prior two approaches. This approach puts a buffer around the line between activity locations, and/or buffers around the end points between locations. This approach is better at capturing the potential of different locations, and it requires at least two locations. The result is an irregularly shaped polygon (see figure). Similar to the prior *line* approach this technique can account for underlying street network. It has been used to study journey to school patterns [129, 167, 201].



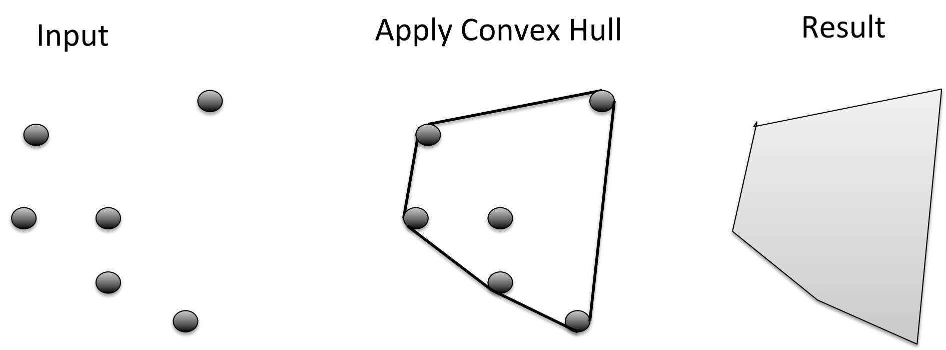
Note: The entire figure is one polygon. The points would not be included.

4. *Point process spatial clustering* - There are various techniques for this approach, but the most common is standard deviation ellipse. This technique might be used to cluster a series of different people's spatial footprints (i.e., a crime hot spot). Or, this technique might be used to understand 3 or more locations for one individual. The result is an irregularly shaped buffer polygon. The shape of the polygon can be varied based on the point pattern and the underlying population or land use characteristics. For examples see: [236, 174, 204].




Note: Figure is based on a graphic from ESRI.

5. *Convex hull* - The last approach is a convex hull - the area of a set of points as bounded by an elastic band. It could be considered a subset of the point process approach. This approach from computational geometry creates a polygon from the smallest convex of a set of 3 or more points [67]. One drawback of this approach if followed exactly as a convex hull is that it misses locations on the other side of the street when constructing the polygon. For examples see: [29, 78].




All of these approaches are interested in how different activity locations of one individual person are clustered in space together.[4] Three distinctions are notable about this literature: 1.) The timing and temporal aspects of this process are almost always absent, 2.) The distribution of other opportunities is not a part of the analysis, and 3.)

[4]The latter two approaches could also be used for multiple people as well.

The focus is almost always on individual activity patterns.[5] For the first issue, when determining the clustering of people at a location, people are always assumed to be located at this particular location regardless of the time of day. A similar issue relates to the criminology literature on hot spots. In essence the focus is on defining a spatial area and not on explicitly determining when an area is hot with activity.

For the second issue, the selection decision for where people go and the range of potential locations are often not a part of the analysis. In a sense, the most common approach in the literature is to observe the movement pattern and make inferences, but less understood is how this movement pattern was chosen from a set of alternatives. The selection process is not a part of the analysis. Although the *accessibility* of different entities has a long literature in geography [116], little work examines how people make decisions about which entity to choose when confronted with a range of possibilities. This is an issue that I address in the next chapter of my dissertation.

In regard to the third issue, all of these approaches focus on individual activity travel patterns. Classic research in geography has suggested that individual paths may be grouped, bundled, and choreographed together [76, 172] to suggest joint interdependence among spatial footprint patterns. Little empirical work has actually tested this possibility. Research in this area has examined how a *cohort* of people is interrelated (i.e., studying people's movement patterns with cell phones).[6] The next step that I take in my dissertation is to examine how the *population* of movement patterns has consequences for neighborhoods.[7] Nonetheless, most of the literature assumes an individual decision maker

[5] All of these different approaches also do not account for substitution effect (use a different location type when near another location) and multi purpose trips. Finally, one methodological critique of this body of work is that it is often unclear how representative these activity paths are for other activity paths in the city. Typically due to data collection challenges, the samples are nonrandom convenience samples and have little to no validation.

[6] One area that needs more attention is how representative these cohort studies are of the population they are intended to represent. Most these studies use convenience samples, and it is unclear who they represent.

[7] Another approach might examine the spatial clustering and overlap of an individuals spatial footprints for a variety of activities. For example, do work trips cluster with restaurant trips? This might be conceptualized as a *spatial multiplexity* of trips. Ignoring the directional component to travel, correlations between distances or factor analysis would be a way to approach this multiplexity.

and little to no emphasis is given for how these activity patterns are a function of other people, different activities, or the urban landscape.

### 2.2.2 Urban Sociology

Whereas geographers might focus on questions of accessibility, scale, and constraints to activity patterns, sociologists arguably focus on the process of constraints via race, class, gender, and power.[8] Geography is often concerned with physical distance, while much of sociology's contribution to work on spatial footprints revolves around social distance. Social distance refers to the idea of differences in various social categories (e.g., race, age, gender, income) between groups of people, and these differences are expected to have the consequence of less social interaction between groups [82, 171]. As suggested by the geography literature, spatial footprints are determined by a variety of *constraints* and *attractions*, but sociology focuses on how various social characteristics (i.e., income) impact individual's spatial footprint patterns. As I now discuss in the following paragraphs, the constraints to people's spatial footprints are often implicitly a part of the spatial mismatch and spatial isolation literatures in urban sociology and economics, while attractions are often employed by scholars suggesting a community of limited liability.

The spatial mismatch literature has focused on job trip patterns to suggest that race and economic inequality constrain individuals' accessibility to jobs. In this literature, low-income and minority groups travel farther to work than other groups, and this distance is a barrier to obtaining and maintaining employment. As a result of a lack of access to outside areas, minority and low-income groups are expected to be socially and spatially isolated from the rest of the city [105, 106, 102, 158, 232]. In contrast, others have suggested that minorities actually have better access since they are physically located in more centralized downtown areas and the issue is race and not space [44, 55].[9] One way of

[8] The geography literature has also focused on a variety of different types of trips, while much of the sociological literature only focuses on jobs or school commuting.

[9] Similarly, all of these approaches to capturing social isolation are explicitly spatially defined, but implic-

conceptualizing social and spatial isolation is by examining people's spatial footprint patterns [127, 132]. As I discuss in the next chapter, social and spatial isolation may be a result of self-selection (i.e., seeking social similarity and homophily) in one's activities, but also a form of segregation from the rest of the city.

Other work using cell phones has operationalized various segregation indices over the course of the day using mobile phone data and simulation data in tandem [164].[10] One study simulated individual's movement patterns and found that these movement patterns were largely consistent with Census tract boundaries [164]. This finding suggests that tracts may actually encompass many individual spatial footprints. This finding is implicitly the approach in the "urban village" model to neighborhood processes that suggests in the extreme that all activity is confined to one area.[11]

To the extent that one neighborhood does not provide all the needs to residents, people might be attracted to other neighborhoods [74, 73]. Scholars have suggested a *community of limited liability* where neighborhood boundaries can be understood as being permeable in the sense that residents will move to and from other neighborhoods for a variety of reasons [70, 71, 100]. This suggests that some neighborhoods and their boundaries have more *social porosity* [88]. People travel outside of the local neighborhood for a variety of reasons, including involvement in neighborhood organizations, school, religious activities, work, or simply finding services that are not within their own unit [93, 94, 150]. This is all to suggest that residents will not be constrained within only one neighborhood. At the same time, the home location is a natural anchor for spatial footprints because of

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itly these patterns suggest processes with a social network component for access to jobs [49] and preferences for location of housing.

[10] A few findings are of note from the cell phone and pager literature. First, there s almost always an explicit focus on individuals movement patterns, which effectively misses the larger choreography of people's movement patterns. Second, the timing of different activities has a habitual pattern, and many of the same locations are visited regularly and repeatedly [165, 65, 209], although the weather does affect people's activity patterns [90]. The data suggests a rhythm to activity patterns, but unfortunately the specific types of activities are often unknown in that people are moving around, but it is not clear exactly what they are doing. Third, most of this research is interested in data collection and computation, and there is little theoretical emphasis for spatial footprint patterns.

[11] This study also found the residential segregation patterns closely mirrored segregation patterns based on individuals' simulated movement patterns.

residential tenure, individual duration in these spaces, social ties, and investment in home and the nearby area.

### 2.2.3 Social Networks

People changing locations over time implies a more nuanced understanding of social isolation, exposure, and convergence. In this way, social isolation and exposure are spatially and temporally dependent upon the locations of an individual in relation to their social ties. While most of the discussion thus far has focused on one individual person, the networks and space literature is a consistent reminder that people are interconnected and interdependent through their networks and social ties, and these ties exist in social and geographic space (for overview see [3]). The burgeoning literature on space and social networks has implicitly examined the spatial footprint of people. Research has shown that at larger spatial scales, much of network structure can be represented with physical distance [32]. In this line of research, distance between people is a strong determinant of whether or not they will interact, as well as homophily and social distance preferences [38, 61, 62, 89]. One challenge for this area of research is its focus on the static residential locations of people. Given that people travel around, the convergence of people coming together to form new ties or maintain social and other types of ties is unknown.

Face-to-face interaction necessarily implies joint convergence of spatial footprint patterns to a similar location, and thus the spatial distribution of people's social networks will shape spatial footprint patterns. For example, Grannis (2009) suggested this idea by essentially arguing that the spatial distribution of street networks determines whether people are tied or not[68].[12] Nonetheless, this study by Grannis and the vast majority of research in this area almost always focuses on social network processes (i.e., tie formation, consequences of ties) as entirely based on the residential home population. Given that people spend time outside of their residential neighborhood (e.g., with work colleagues, family, friends in other

[12]Whether or not a tie forms between two people is also arguably dependent on spatial footprint patterns and the set of potential ties.

neighborhoods), this suggests that the home location may not be the only location to understand social network processes. Spatial footprint patterns allow for insight not just whether ties between people exist, but also how they situate people to interact over the day.

One implication from this idea is that different spatial footprint patterns may be related to different types of ties. This suggests a distinction for different types of spatial footprints. The geography literature makes a distinction between two different types of trips [111]: obligatory trips (i.e., work) and discretionary trips (i.e., shopping). Social networks are likely tied to discretionary (amenity) trips, such as meeting with friends at a restaurant, rather than obligatory trips, such as school or work. While social networks may have aided in the job search process or what school to attend, these processes have already occurred when examining daily spatial footprint patterns.

Another approach suggests that the history of where people have lived (i.e., prior residential locations) might shape spatial footprint patterns. For example, friends or a particular business in another part of the city might draw people to these more distant spaces. This implies that areas with more residential turnover may in fact have ties to different areas of the city. Whereas neighborhood research most often suggests residential turnover within a neighborhood is a detriment to local ties within the area, it might also be the case that neighborhoods with more turnover have residents who are tied to more areas of the city (i.e., if you move around more, you might have more ties in different locations).[13] In this way, residential turnover in an area might be associated with a larger geographic spread of social ties to other neighborhoods. At the other extreme, residentially stable neighborhoods also have the characteristic of having much more familiarity, better chances of forming ties, and perhaps prior experience addressing problems in the area. This suggests that residentially stable communities have a smaller geographic footprint.[14] This pattern would suggest that the longer someone lives in a neighborhood the shorter the

[13] This approach necessarily complicates conceptualizations of only examining ties that exist within the local area.

[14] On the other hand, more wealthy areas are more likely to be residentially stable. Wealthy areas may have a greater reach in their ties by having an easier ability to travel (i.e., more money, more leisure time).

geographic distance of their social ties, while those in neighborhoods with more population turnover may have more distant ties.

Social ties to other people implies knowledge of other neighborhoods and areas of the city, even if a person has not traveled to those locations. For example, people living in the same household might inform each other of a place with high disorder or a neighborhood to avoid. This knowledge might change someone's spatial footprint pattern even if they have not visited this high disorder location. Perceptions of different parts of cities and entire cities themselves might be avoided because of other people's perceptions. Ties to other people may provide knowledge about where to go and other activities within the city. The knowledge and information gathered through the spatial footprint of a person's social ties may give an individual information about the general area.

### 2.2.4 Criminology

The next section of my dissertation discusses criminological theory in regards to spatial footprints. For decades, neighborhood theory and empirical work has bracketed each neighborhood to processes within only it's boundaries, and this isolates community processes within the focal area [229, 230]. By assuming a restricted spatial footprint of residents throughout the day, researchers, police, and policymakers are working under the assumption that the social and spatial criminogenic neighborhood processes are only the result of neighborhood residents and is the same at all times of day.

In what follows, I discuss several criminological theories and how they might matter for understanding daily crime patterns. My focus here is on opportunity, environmental, and control theories because they are the most commonly employed approaches for neighborhood research. Other criminological theories are applicable to the spatial footprint approach though. Strain, biological, and peer theories all implicitly likely require a spatial footprint process as a part of the theory. For example, the social influence process of peers, the strains of a person and their expectations from their environment, and how biology matters is dependent upon the context in which it unfolds and the availability of other people in space and time. In other words, spatial footprints help to situate the social influence of peers (presumably peers need to be coincident (i.e., occurring together in space and time) to provide influence), expectations for strain might form through spatial footprints, and biological hard wiring is not absent from space and time. In other words, the various theoretical mechanisms do not just exist, but in fact interact, mix, and move around in space and time.

### Social Disorganization and Collective Efficacy

Shaw and McKay's (1942) classic work in Chicago suggests that neighborhoods with residents who are more racially similar and who have lived in the local area longer will have less crime because inhabitants have greater trust among each other, and accordingly more informal controls to suppress crime [31, 84, 203, 222]. Social disorganization theory suggests that the economic disadvantage, ethnic heterogeneity, and residential instability of a neighborhood limit residents' social networks, which in turn leads to increases in crime. Sampson and colleagues' work on another seminal project in Chicago extends social disorganization theory by examining the collective efficacy of neighborhoods. Scholars in this tradition argue that it is residents' perception for mutual support and their willingness to intervene as the most salient factors for inhibiting crime and suggest that social ties are a necessary component for crime control [51, 142, 188, 189, 190, 192, 193].

The workhorse of social disorganization and collective efficacy theories is informal social control: a person or group's ability to intervene and actually stop a criminal event [31, 203, 222]. However, the majority of neighborhood criminological research has examined the *potential* for social control rather than the *actual* social control in neighborhoods [211]. Most research in this tradition uses data that assumes residents are always in their home neighborhood and *available* to restrain crime. Assuming someone is available within a space during a particular time, his or her *presence* might be simply enough to prevent a crime.[15] In a sense, for these theories to effectively explain actual restraining behavior of delinquents, the agents of control at a minimum must be spatially present at the right time to control crime. The spatial footprints of residents allows insight into whether people use different spaces throughout the day and how these patterns impact their availability to control crime in their neighborhood.

Many people who visit a neighborhood do not actually live there [125]. Sastry, Pebley, and Zonta (2002) use the Los Angeles Families and Neighborhoods Study (LAFANS) to show that residents travel 1.37 miles on average to the grocery store and 8.15 miles to work, which is much larger than the size of the average Census tract. Similarly, the National Household Travel Survey (U.S. Department of Transportation 2008) suggests that high school children travel an average of 6 miles to school. As residents move throughout the city over the course of the day, they will gain exposure and possibly ties to areas outside of the focal residence. These movement patterns will likely fundamentally change the ability of a neighborhood to control crime on a daily time scale.

Through a sustained presence in an area outside of the home, such as a work location, people from outside the area could possibly have some investment and form ties in their "work" neighborhood.[16] These locations outside of the focal residence and the surrounding area might serve as a natural anchor point for connecting the home neighborhood to other parts of the city.[17] For example, one study from the geography literature suggests that work locations provide more potential for social interaction because of the concentration of people [60]. This "choreography" and "synchronization" as indicated in the geography literature [76, 172] suggests that different neighborhoods will become intertwined as residents travel and spend time throughout the city over the day, week, and season.

Through a person's relationships and different activity patterns, residents' social ties

[15] Other scholars have built on this insight by examining whether people are willing, capable and able to perform actions of social control [180].

[16] To the extent that residents of the focal neighborhood are unwelcoming to others from outside of their boundaries, this also might stimulate conflict due to competition over resources (e.g., jobs).

[17] Research also has suggested a *community of limited liability* [70, 71, 100].

may have a broad spatial footprint outside of the local neighborhood. With activities in other neighborhoods and ties to other people, the neighborhoods of the city become interdependent as residents travel around to different areas. One study suggests that distant ties outside of the neighborhood are associated with less cohesion in their home neighborhood [17]. To the extent that people are more invested in places outside of the home neighborhood, such as a work location or near a friend's home outside of the neighborhood, this may suggest less cohesion and collective efficacy in the home neighborhood, in part because the spatial footprint of their ties pull them outside of the local area. In the work neighborhood, however, the sense of community among work colleagues may serve as another form of social control and collective efficacy. For example, if the work colleagues spend time after work together or during lunch breaks outside of the focal block, this may suggest a broad spatial effect of the benefits from these social ties.

### Routine Activities and Environmental Criminology

Routine activities theory argues that crime occurs where and when everyday life happens [42]. This approach suggests that crime occurs when a motivated offender comes together with a suitable target in the absence of capable guardians (for extensions of this line of work see [12, 36, 43, 53, 152, 153, 162, 178]).[18] Depending on the time of day, some parts of the city will become excluded or activated as a function of the daily shifting patterns of people in the city. For example, to the extent that people leave their home neighborhood and travel to work, their vacant home may be particularly susceptible for crime [42]. This implies that the guardianship of a neighborhood changes throughout the day, but this is rarely tested.[19]

[18] Eck and colleagues (1995) added to this framework by specifying more specific types of guardians, including "handlers" such as parents to restrain offenders and "place managers" such as bar managers to control places.

[19] Routine activities theory has mostly focused on the perspective of offenders thereby implicitly discounting the impact of guardians. Moreover, the agents of social control from social disorganization and collective efficacy are arguably the guardians, handlers, and place mangers in routine activities theory. In a sense, they would likely do the same task of stopping offending behavior [84].

More recently, routine activities theory has been paired with environmental criminology, an approach to crime analysis that focuses on *where* crime occurs and how physical aspects of the area (e.g., street lighting) impact crime rates.[20] Going beyond a model that is strictly tied to a single neighborhood, Brantingham and Brantingham (1981) have suggested that offender activity spaces, the spaces where people spend most of their time, will serve as the nodes within their larger activity space. Therefore, crime is most likely to occur within these nodes and paths between them [19]. Although it is unclear how the rhythm of individual behavior translates into broad patterns of crime within and between neighborhoods, these approaches suggest that it is within a person's spatial footprint where crime is most likely to occur (see also [229, 230]).

The journey to crime literature has focused on one distinct type of spatial footprint activity (for a review see [185] and [178] for journey to work and crime). Drawing from Horton and Reynold's (1971) activity space concept from geography, Brantingham and Brantingham (1981) have suggested that offender activity spaces, the spaces where people spend the most of their time, will serve as the nodes within their larger activity space. Crime is most likely to occur within these nodes and paths between them [19]. These approaches suggest that it is within a person's spatial footprint where crime is most likely to occur. Wikström (2012) uses travel diary data from the Peterborough Youth Study to examine individual youth's activities over a 4-day period [230] (see [40] for visualizations). When tracking people's journey to crimes, they find that only 9% of offenses occur at or near the home, 18% at school, 9% at a best friend's house, and the remaining are in other areas throughout the city. Using the same data, Bernasco et al. (2013) find that youth offend when they are most often in the presence of peers, absence of adults, in public, using alcohol and out of school [13]. Similarly, research on co-offending, which is suggestive of a convergence of spatial footprints of at least two people, indicates that 5.7% live in the same school district and on average live 4.9 miles apart [197, 198](see also [166]). Most often

[20]Similar to routine activities theory, this approach is conceptualized largely from an offender's perspective and there is little emphasis on the impact of guardians for controlling behavior.

these approaches are explicitly interested in comparing individual offending patterns, and none of these approaches look at broader patterns of youth and the interdependencies of their activity patterns. Drawing from routine activities, this line of research has yet to examine how the spatial footprints of potential guardians impact crime in neighborhoods. For example, even if the number of offenders increases in a neighborhood, this will not impact crime to the extent there are enough capable guardians nearby. One of the fundamental gaps that I address in chapter 5 is identifying the spatial distribution of potential guardians throughout the day and the impact of their spatial footprints on crime.

Along with the journey to crime literature, research has also examined how exposure to different areas puts people at risk for committing crimes and becoming a victim of a crime. Exposure to violence on a youth's journey to school has been shown to have negative consequences for school achievement [202]. Drawing from the social isolation argument discussed earlier in the urban sociology literature, a small qualitative study of youth in South Africa suggests that youth's spatial footprints are constrained to disadvantaged areas, and this puts these youth an increased risk for victimization [135]. Ceccato (2014) has noted the activity patterns of subway stations and how these patterns relate to crimes nearby the stations at different seasons and holidays [39]. Browning and Burrington (2011) highlight that individuals are exposed to multiple contexts, which is one implicit consequence of spatial footprints, and in particular their home neighborhood and schools. Their approach simultaneously considers youth exposed to both of these contexts to examine whether or not an individual has committed a violent offense [24]. Given that locations are mutually exclusive in that people can only be in one at once, one challenge for their study is that it is unclear where the individual committed the violent offense (i.e., at home or school), and when an individual was actually located within the school or home neighborhood. A similar issue also occurs when considering whether it is something about the area where crime is clustering, the residents that use the area during the day/evening, or the change in the characteristics themselves. This is all to suggest that spatial footprint patterns may make some neighborhoods more attractive for crime by changing the presence of targets, guardians, and offenders.

When discussing routine activities theory, many scholars highlight several common critiques [120]: 1.) Who are targets, offenders, and guardians? 2.) Where do targets, offenders, guardians come from and how do they converge in space and time? 3.) The issue of multiple group membership: sometimes a person is an offender, and other times he/she is a target. One major challenge for this theory is identifying the guardians, offenders, and targets. Research from crime pattern theory and routine activities theory suggests that what offenders do most of the time is similar to people who have not offended [19].[21] This makes it quite difficult to identity an offender from anyone else in the population, and this is the group that often gets the most attention. The offender thus only becomes evident once a crime has been committed (i.e., post hoc).

With that issue in mind, even if we could identify these "types" of people, we still have the second issue noted earlier: where do they come from? As Cohen and Felson noted, they assume that targets, offenders, and guardians have converged (or not converged) together in space and time for a crime to occur. This raises the issue of *availability*. The spatial footprint of people fundamentally determines the availability of people at particular spaces for different times of day. For example, when understanding crime patterns over a year or longer patterns, homeowners are expected to be associated with less crime in part because of their investment in the area, residential stability, and potential ties to the area. When considering whether this homeowner is *available* during the day, this process is more complicated and often it is assumed that the homeowner is always available as a guardian [180].

These issues raise a question: when considering the general population, what group are most people expected to be a member most of the time? If people can control crime with just their availability, this suggests that most people (i.e., the vast majority of the

[21] Similar to almost all criminological theories, this approach implies a model where people are constantly offending, guarding, or being targets.

population) are guardians. Even if we are assuming there are targets and offenders, these groups represent an extremely small slice of the overall population in part because crime is a rare event. As I discuss in chapter 5, spatial footprint patterns may help to give us insight into where these groups come from.

## 2.3 Challenges for the literature

The literature on spatial footprints highlights the challenges for assessing how context matters. One takeaway from the literature is that people are exposed to and experience multiple contexts throughout the day and over the life course [125, 140]. This approach recognizes the importance of not only considering where individuals sleep and live, but also where they spend their time. As dynamic movement patterns that are shaped by physical distance and social distance, the spatial footprint approach recognizes that not everything is equally accessible in space and time; there are constraints to spatial footprint patterns; and some areas are also more preferable and attractive than others. In the next three sections, I highlight three general issues with the spatial footprint literature that I classify as: 1.) Interdepdence, 2.) Temporal Processes, and 3.) Spatial Processes. While I discuss each issue in separate sections, they are all fundamentally interrelated and often conceptually blend together.

### 2.3.1 Interdependence: Individual and Independent Units

Much of the empirical literature on spatial footprints largely conceptualizes them as a function of independent individuals making decisions. Each individual spatial footprint path is essentially a unique trajectory in space and time. In this view, individual people travel around to different activities and routines, and people are assumed not linked together. The theory for movement patterns for groups of people and different spaces of the city is largely absent from this work. The focus is often on whether something is more or less accessible to a person, the constraints limiting access to something, and what makes some locations more or less attractive. Most often research in this area is conceptualized as a tethering process where individuals travel about and return to home. While research on spatial footprints highlights that individuals are mobile in space and time, much of the environment around these footprint patterns is treated as static or irrelevant. In the literature, the individual and the environment - family, peers, strangers, and neighborhood - do not move and change in concert together. While most often found in cohort studies, and arguably appropriate for some research questions, this implies a social world where there is little to no interdependence between spatial footprints, social networks, neighborhoods, activities, or other social processes by assuming independence of actors.

Rather than focusing on independent units, the spatial footprint approach focuses on how different social processes relate to broader activity systems - joint and interdependent patterns of people's collective behavior in space and time. Embracing a model of interdependence, the city, its neighborhoods, and individual people can be conceptualized as a social system. While Hägerstrand (1970) suggested that spatial footprint patterns are "bundled" together, little to no work has examined this possibility. Even still, when groups of spatial footprints are examined in concert, research to date only examines these bundles as a function of social ties between people (i.e., using cell phones to track a meeting between friends). In other words, the focus is only on other people known in the study sample. Other people (i.e., strangers) in the environment are not a part of the conceptualization or analysis. For crime research, these strangers may be particularly important if simply someone's presence can prevent crime.

Another advancement of the spatial footprint approach for the literature is that it considers the broader implications of these "bundles" for the state of the city at a particular point in time. This is a considerable distinction from prior work. As one example, rather than focusing on how students and a teacher have coincident spatial footprint patterns at one particular school, I am interested in understanding the shifts in the population from home to school for all schools in the city in the morning. In this way, my conceptualization of spatial footprint patterns for cities is more holistic and akin to a demography of daytime activity. Embracing the city as a social system suggests focusing on spaces of the city and how people within these spaces change over time.[22] By viewing the city as a social system, the spatial footprint approach considers how, when, and where different neighborhoods are more or less activated as a function of the population density shifting to other areas of the city for different activities at different times of day. In this dissertation, I examine spatial footprint patterns of people moving between different neighborhoods, and how these patterns have consequences for neighborhood research.

The issue of independent units is not strictly a problem for research on individuals. The neighborhood literature often conceptualizes a social world of discretely packaged individual neighborhood units. While due in part to data collection challenges, the "neighborhood effect' is often only captured as the demographic characteristics of one census tract. The spatial footprint patterns of people suggest that people spend time in other neighborhoods.[23] When people travel to different neighborhoods, the city's neighborhoods are no longer independent units. In line with this idea, Hipp and Boessen (2013) recently created a new measure of neighborhoods - *egohoods* - in which neighborhood units are explicitly spatially interdependent and overlapping [86]. While conceptually more appealing, this approach was also shown to do a much better job at explaining crime rates across several cities than approaches that use discrete individual units.

The overlapping egohoods approach is primarily a spatial conceptualization for interdependent and overlapping units, but as Hägerstand noted long ago, space and time are fundamentally linked together. Egohoods were motivated in part due to the spatial

[22] Kwan (2009) has suggested only focusing on people based measures, and eliminating place based measures of areas because of people's movement patterns [123]. Part of the reason place based measures are important is that much of life is still geographically based, but also because place based measures provide some insight to what else is going on (e.g., other people in the context).

[23] When considering the spatial footprints of individuals, this implies people moving around to different neighborhoods. The independent units approach arguably hinders conceptualizations for the relationship between micro and macro processes. Most work to date on spatial footprints almost exclusively focuses on micro processes.

footprints of individual people traveling around to different neighborhoods during the day. The approach is conceptualized as a joint exposure model to multiple neighborhoods, rather than situating when people are actually located in different spaces of the city. With people moving about to different parts of the city, the cause and consequence for a variety of social processes are always assumed to be concurrent in space and time.[24] As such, this overlapping *spatial* unit model ignores the *temporal* unfolding of the social process, and when people are actually located in different spaces.

### 2.3.2 Temporal Processes: Time Scale and Temporal Sequencing

The spatial footprint literature most often considers where people are located and less emphasis is given to the unfolding, sorting, and ordering of different contexts over time. With new data collection methods allowing for continuous monitoring of social entities (i.e., cell phones and sensors), the challenges for unpacking temporal processes for spatial footprints need more attention. Four main issues stand out for this literature: 1.) Causal flow and ahistorical social processes, 2.) Sequencing of different activities, 3.) Concurrent factors are the only causes, and 4.) Time scale of different social processes. I now discuss each of these issues below and their connection to spatial footprint research.

For the first issue, spatial footprint patterns of people are often ahistorical and are not situated within any particular social context. As Abbott (2001) noted, much of social science lacks a clear causal flow for the process of interest [2]. Following Abbott, social science and spatial footprint patterns are often treated as emergent phenomena that do not have any history or anticipation of the future. The city and social life is ongoing and unfolding, but it is unclear how different people's spatial footprints are situated within time. The unfolding of spatial footprint patterns reminds us that not all resources, ties,

[24] One challenge we faced when creating egohoods was the size of the buffer around a block. The spatial footprint is one approach to theoretically and empirically determining the size of the buffer.

and other things are equally activated and accessible at the same time, but also that there is a temporal ordering to social processes. Spatial footprints need to be considered within the time period that they are occurring.[25]

In regard to the second issue, the temporal sequencing of social processes, research on spatial footprint patterns assumes that the ordering and sorting of different activities and footprints do not matter for understanding the social phenomena of interest. While Abbott (2001) first used the term "sequence" to describe the general ordering of social processes, this idea is applicable to spatial footprints. Spatial footprints are dynamic processes, and one consistent finding from various travel surveys is that many daily spatial footprint patterns, particularly for obligatory trips, are habitual, routine, and occur at regular time intervals [20]. Habitual spatial movement patterns are clearly distinct from conceptualizing a static social world. The routine convergence of multiple individuals in space suggests interdependent spatial footprint patterns, but also a need to think more seriously about temporal processes, particularly the ordering of different routines. Most often the entire set of spaces visited for a footprint are aggregated together to form a path area, or we only examine one particular state of the system.

As one example, Census data captures characteristics of respondents in their residential areas over the months of data collection (the spring) for one particular year of a decade. While exceptionally useful, the Census arguably most closely aligns with what might be thought of as the "nighttime" state of the neighborhood, which of course is only one state of many possible states that this measurement could have taken place- summer, morning, lunchtime, Saturday night. With different states of social systems, this implies spatial footprint patterns to change the underlying potential for different social processes and that there is an ongoing sequencing to their occurrence. The sequencing between different spatial footprint patterns might allow for the development of face-to-face social influence

[25] The change in spatial footprint patterns over decades might also suggest changes in neighborhood processes. For example the changes in the crime rate and subsequent crime drop in the late 1990's may be associated with changes in spatial footprint patterns.

and social control processes.

The third issue focuses on the time scale of different social processes. The spatial footprint approach that I take here focuses on short-term daily movement patterns. This of course does not necessarily mean that short-term and daily processes are the only ones of importance.[26] The proposed cause of some effect may often be due to the temporal scale at which the process is measured, and the process of interest may be unfolding over differing time scales, including hourly, daily, weekly, and yearly [2, 48]. For example, crime patterns in cities might be understood as a function of residential instability in some areas, and this process implies a particularly long time scale. Other processes such as social influence with peers implies a much shorter time scale for when peers are in face-to-face contact. With the mobility of people to a variety of social contexts over time, the "cause" of the current situation is less clear. The "cause" of some social phenomena is unclear as being explicitly due to something during the current hour, earlier in the day, last week, last year, or even much slower over the last decade. All could potentially be at work.

The fourth and final issue in the spatial footprint literature in regard to temporal challenges is its focus on concurrent "causes": the social process of interest is only a result of factors within the current situation. A growing area of criminology focuses on situational causes of offending [13]. This approach suggests that the immediate and concurrent environment causes offending. One gap in this area is how the prior environment might matter for the current environment. As one example, when examining a prisoner's behavior while in prison, we discovered that people's neighborhoods on the outside of the facility mattered for their behavior while inside the prison [15]. One question this raises is the challenges of specifying the temporal range of "prior." At one extreme, a life course perceptive is that "prior" represents birth until the current situation.

Another approach would suggest some immediately prior discrete time point (e.g. last

[26] On a longer time scale, the rate of change for different areas might also be important. Gentrification and concentrated construction within some neighborhoods might be suggestive of an area of the city that is changing much faster than other parts.

year). In this approach, research will often include a 'lag' of the previous time point to capture the starting point of the process.[27] The idea is that last time point is a good predictor of the current time point, and we want to examine what factors lead to the change between this year and last year. But, less clear is whether there are more micro temporal processes or longer-term processes over decades at work. Rather than a yearly time scale, this process gets more complicated on a hourly, daily, and monthly time scale. Would yesterday predict today? Do weekdays explain weekends? Last Thursday predicts this Thursday? This morning predict this evening? This variation suggests differences about how people's spatial footprint patterns unfold; otherwise the expectation is that they are static and constant in one residential space.[28] The previous time point may not be the best explanation for the current time point in part because the prior time point does not necessarily place people in the same spaces.

Rather than a focus on some previous time point, I suggest temporal units be grouped together based on different *activities*, and this approach would focus on the prior activity. As suggested by various travel surveys, daily life is fluid, yet structured and habitual. At the same time, social processes are often not neatly packaged into discrete time units. As one example, children spend much of their time at school, but also at home. If we examine micro hourly temporal units, we might only capture when children are at school. After children have been at school for several hours during the day, it would likely be inappropriate to only suggest that the "cause" of some behavior in the afternoon is only dependent on the previous hour. The prior school day, home environment over the last year, and last evening might all operate as "concurrent" factors.[29] Rather than focusing on

[27]Similarly, there is the tendency in criminology to take an average of several years of data to minimize fluctuation over years. While this might be necessary for statistical necessities or particular research questions, it is not necessarily the only approach or even the most theoretically interesting. The fluctuation over time is arguably an interesting part of the process.

[28]This question is somewhat similar to processes that focus on how much changes in *city* crimes are due to *neighborhood* changes or some other change process. We have little understanding about the rate of change in different neighborhoods. How quickly is a neighborhood changing? Are all neighborhoods changing at the same rate? Work on aging in place and the life course suggests that they are not.

[29]These issues are arguably even more challenging for more continuous time data patterns (e.g., always monitoring through sensors). Nearly all social science research conceptualizes entities in discrete non-

each hour of the school day, we might consider the entire school day as a temporal unit: Monday through Friday, 8 am to 3 pm every season except summer. In this view, space and time are both interesting and interrelated components for interdependent social phenomena. In chapter 5 of my dissertation, I use this activity approach when predicting neighborhood crime.

### 2.3.3 Spatial Processes: Spatial Distribution and Urban Form

For the much of the social sciences, geography aside, space in relation to social processes are often not a part of the analysis. The geographic landscape where spatial footprints take place may offer clues for how a social process might play out. Similarly, we almost never examine the social process of interest in action, but look at the potential where some process might occur (e.g. collective efficacy, social influence), and with this in mind, the physical geographic landscape may be at least as important for understanding the process itself. In regards to spatial footprints, there are at least four gaps in this literature: 1.) The distribution of the activity structure, 2.) Land uses, 3.) Constraints and enabler characteristics, and 4.) City and regional effects. I now turn to each of these issues.

In regards to the first issue, the distribution of the activity structure, spatial footprint research most often tracks people's movement patterns over time (e.g. where you go over a day), but less clear is how the structure of availability opportunities shapes these movement paths. One challenge for this literature is that only the "destination location" or where people end up is observed. The selection decision related to why people go where they go is lost in the analysis.[30] This underlies a need to understand spatial footprint patterns, the characteristics of where people decide to go out of a range of different activity locations, and the selection process by which some areas are more or less accessible. By examining where people could go and do not go, we gain an understanding of people's daily

overlapping temporal units, rather than an understanding of time as a continuous process.

[30]The choice process of the decision to take a trip is assumed to be independent of where people decide to go.

lives, and more implicitly the characteristics that directionally bias spatial footprints. For example, if people prefer social similarity and little social distance then this suggests spatial footprint patterns where people avoid heterogeneity and seek similarity. The spatial distribution of where people could go, actually do go, the characteristics of the people in the area, and nearby area implicitly set the potential for an area's susceptibility/risk for various social phenomena.

The distribution of the activity (opportunity) structure, in other words, the choice set of available alternatives, allows incorporating information on where people could go, not just where they do go. This idea stems from work in geography on the distribution of opportunities (e.g., when searching for a grocery store, how many grocery stores are available in the area?) [64]. The availability of alternatives may set the stage for the social process of interest, but this possibility is rarely empirically examined. An individual's ability to gain employment is one example. Traditional individual and macro characteristics - SES, discrimination, skill set, contacts, economic market and a host of other characteristics - might all play a role in whether someone gets a job. These characteristics all exist in space and are likely spatially clustered. Even still, the number of jobs and the distance (social and physical) will determine the opportunity for employment.[31] The spatial distribution of opportunities suggests varying availability and distinct spatial differences for spatial footprint patterns.[32] Most often these "background" factors are all implicitly assumed to be irrelevant even though they arguably are a major part of the social processes of interest.[33]

[31] Another example would be where children go to school - most often there is one potential school location, rather than numerous available alternatives.

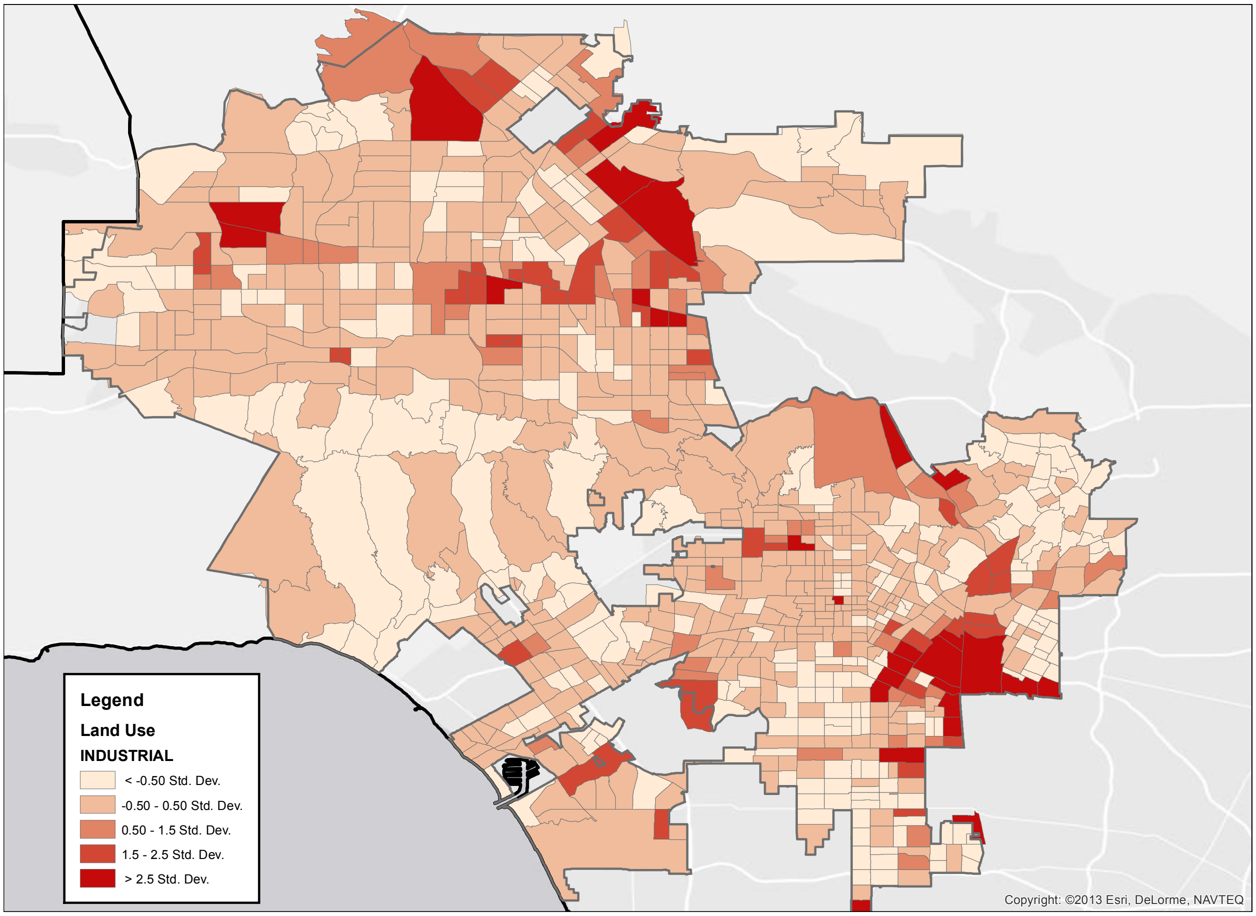
[32] The distribution of the activity structure suggests the importance for the spatial scale of different social processes [5]. For example, different modes of transportation suggest distinctions in the spatial scale of spatial footprints. The area that someone could potentially cover in some allotted time is different for walking, driving in a car, on a train, and in an airplane.

[33] One example is the presence of racial bias in police arrests. While the police might arrest one racial group at a much higher rate, the baseline expectation for this rate of arrest is in part a function of the spatial distribution of this population in the area (and the rate of criminal activity). To show a bias, we would need to go above and beyond this baseline rate. A similar argument is sometimes made when examining racial segregation processes. Some of this distribution is due to discrimination and personal preferences, and some of it is also due to the racial composition [33].

As for the second point, the land uses of the city and their *uneven* distribution implicitly situate where and when different spaces of the city are densely populated, as well as the availability of different opportunities. With considering alternative destinations, we can start to unpack individual and group processes. The baseline background template and "potential" for social processes is likely dependent upon the spatial and demographic characteristics of the area. The clustering of spatial footprints may help to situate individual and group processes. The spatial distribution of different land uses in the city helps us to implicitly situate where different people are located for a particular point in time since they are not all actually being used at exactly the same time. For example, an area with industrial and office land uses have much activity during regular businesses hours, but it is largely vacant on the weekends and evenings. As shown in Figure 2.1, industrial land uses in Los Angeles are spatially clustered to suggest correlated occupation and duration in these spaces. *Appendix A* provides details for how the land use data was collected and coded.

As the figure suggests, land uses are distributed unevenly in their presence (i.e. more residential than retail areas in cities) and their spatial location. For example, a city with one centralized downtown area has businesses and residential areas spatially distributed and concentrated within different parts of the city. Given this city layout, a business is much more likely to be located nearby other businesses, while a residential unit is more likely to be located by other residential units. A concentrated business area is suggestive of greater visibility for businesses than residential areas because it is centrally located within the city and nearby other businesses. A spatially concentrated downtown area has more potential for the spatial clustering of retail entities, than residential areas that are spread throughout the entire city. This is implicitly true due to the fact that business land uses are much less frequent than residential land uses, which are more abundant. The centralized downtown suggests intensity for one area's spatial footprints, and this might have consequences for exposure, visibility, and accessibility.

Figure 2.1: Industrial Land Use, Los Angeles 2008




The third point considers the effect of where an individual or neighborhood is situated within the city and larger region, as well as how the city and regions fit together. This idea is what Matthews (2013) and others have noted as the "embeddedness" of different areas, but almost no empirical work has tested this possibility or examined how this embeddness relates to spatial footprint patterns. The location of spatial footprints is likely dependent on where a neighborhood is situated within the city, as well as the larger region. A city that is surrounded by other cities vs. a city surrounded by farmland might structure movement patterns differently. While in part due to the urban and rurality of a particular area, where someone is situated in relation to the distribution of rurality might matter for where they go.

Turning to the fourth and final point, a consideration of where people go is likely a function of a range of physical constraints to travel and enablers for travel. The street network and transportation networks within a city, mode of transportation, and many other physical barriers including distance, weather, different types of roads, and rivers all could potentially impact travel patterns. One study that tracked people's movement patterns for one weekday found that more street connectivity and more retail land use determined the total distance that someone traveled over the day [59]. As another example, the location of subway stations in the city implicitly might situate where people that ride this subway can go and cannot go, and in many neighborhoods of cities, there is not any access to public transportation. While these differences might implicitly be captured in the mode of travel (i.e. car, train, walking, plane), the accessibility and variability in the spatial distribution of where these factors are situated across the city constrains/enables access to different areas of the city and people's spatial footprint patterns.

## 2.4 Consequences of the spatial footprint for crime in daily life

This section discuses the consequences of spatial footprint patterns for crime, particularly neighborhood crime. I focus on daily, day of week, and seasonal crime patterns, rather than long term crime patterns over years or decades. In what follows, I focus broadly on 5 main issues: 1.) Neighborhood boundaries, 2.) Interdependence of neighborhood processes, 3.) Changes in population density, 4.) Informal social control, and 5.) Different types of crime and different spatial footprint patterns.

### 2.4.1 The Elasticity of Neighborhood Boundaries

Defining neighborhoods and their boundaries has long been a challenge for neighborhood research. A variety of units and approaches have been used to define neighborhoods with some explicitly using administrative Census units, social networks, social characteristics in tandem with physical characteristics, and overlapping units [86].[34] Similarly, research using individual people as units of analysis will most often assume no spatial process. When studies do, they most often demarcate some area of influence for an individual person (i.e., a buffer around someone's home), but the size of the spatial area is almost always uncertain and most often only one location is observed. Much of the neighborhood and individual environment literatures conceptualize people's entire world as neatly packaged within static and discrete boundaries [86]. While due in part to data collection challenges, the 'neighborhood effect' is often only captured as the demographic characteristics of one census tract [58].[35]

This raises a question: How should we draw neighborhood boundaries? Ideally, neighborhood boundaries should be developed from theory and dependent upon the process of interest [83, 87]. The determination of boundaries implies a process among residents in regards to *awareness, identification, and agreement* about boundaries. In line with a static boundary approach, it suggests many neighborhoods have known boundaries. In other words, residents are all in agreement and mutually aware of one neighborhood vs. another area. Can people identify the boundaries of their own neighborhood? What about other neighborhoods? What is the gold standard for a neighborhood boundary? This is not to say that boundaries are not real or geographically based, but that they are more fluid and difficult to precisely measure than often given consideration. Boundaries are necessary to

[34]There are generally three approaches used in the literature to define neighborhood boundaries. We might completely ignore boundaries all together and create *egohoods* [86]. Another approach uses administrative units or other groupings from the Census. These boundaries typically form based on the similarity of social characteristics of residents. The Census determines tract boundaries are made with grouping the social similarity (e.g., race) between residents.The extent of differentiation between the units where a boundary is drawn is always assumed to be extremely rigid in that there is no social porosity between the units [88]. For example, we might make a distinction between boundaries that are somewhat soft vs. others that are somewhat harder [86]. Another approach suggests that boundaries form and change over long patterns of time. The boundaries might form through a process of residential migration, demography, segregation, and sorting over years and decades [179, 199].

[35] At the same time, a large body of research has examined the ecological fallacy, the modifiable areal unit problem (MAUP) [161], and the challenges for specifying neighborhood boundaries for various indices [234]. These challenges, however, do not really capture the spatial and temporal uncertainty associated with individual spatial footprint patterns.

some extent in order to have any kind of collective entity [2], but they are often assumed to be absolutely rigid in separating social entities such as neighborhoods. In nearly all neighborhoods research, the boundaries of the neighborhood unit or individual space of influence are almost always exogenous, static, and determined by the nighttime home locations of residents. In a sense, the boundaries are drawn based one snapshot of where people are located.

The spatial footprint patterns of residents may be useful for measuring neighborhoods and their boundaries.[36] A person's location can be understand as having a specific duration in a particular space. With this in mind, I define a neighborhood as: a spatial concentration of people for some duration of time, along with social networks among people. Different people within an area might collectively organize to address a "collective action" problem from time to time. In this way, each resident has a latent potential to collectively organize in response to a collective action problem [86].

With this in mind, I expect neighborhood boundaries to have *elasticity* over the day. The boundaries are expected to change throughout the day in part because of 1.) the spatial footprint patterns of residents and 2.) the needs for different collection action problems.[37] This implies a conceptualization of neighborhoods that are not predetermined, but form as a function of different neighborhood issues, social tie formation preferences, and the availability of others in the area. The footprint of the collective action problem may give rise to the boundary, and the boundaries are not predetermined.[38] The approach

[36] Land uses may help define and understand neighborhood processes. While physical barriers such as rivers, gated areas, and highways and attractors such as parks and lakes have been explored [88, 169], it is less clear what land uses should be incorporated into defining neighborhoods and for neighborhood processes. Do all spaces of the city need to be a part of a neighborhood? Are neighborhoods entirely residential? As suggested by the new urbanism approaches to planning, the urban village model for defining neighborhoods suggests that there would be a variety of land uses within the neighborhood. Jacobs (1961) has argued for mixed-use areas to help bring about social interaction and implicitly neighborhoods [98]. Accordingly, it is not clear if mixed-use represents the structure of a building and the land uses at different floors such as first floor retail and second floor residential, or whether the idea is about some spatial area such as a residence and retail on the same street. The layout of buildings, streets, and buildings heights in relation to different neighborhood processes is largely unexplored.

[37] Time of day, weather, and visibility might also play a role. For example, neighborhoods might encompass a larger area during the day due to more visibility than at night.

[38] On the other hand, there is arguably a bit of a romanticized conceptualization of people coming together

is therefore not explicitly based on the nighttime characteristics of residents, but upon the *spaces* of cities, the duration of people within those spaces over the day, week, and season, their networks, and the particular problem at hand.

### 2.4.2 Interdependence of Spatial Footprints and Neighborhood Processes

Neighborhood change and people traveling to different neighborhoods throughout the day implies a dynamic approach to neighborhood and city processes. At the same time, we have little understanding of the mobility patterns of everyday life and how these patterns relate to different contextual processes [7, 64]. The activities of people will likely be jointly correlated in space and time (e.g., leaving work, entering into spaces during specific times, etc.) and different sets of activities may often move together (e.g. beginning of work and school). These movement patterns can be conceptualized as a web of interacting spatial footprints [64]. As a result, different neighborhood activities and processes are fundamentally interdependent.[39] For example, a large spatial concentration of people during the day, such as a downtown area, implies broad synchronization and coordination among people from many different parts of cities. These kinds of changes imply at least two main consequences: 1.) interdependence of different neighborhoods through spatial footprints and 2.) changes in the population density of different areas of the city. This section focuses on this first consequence.

The interdependence between different neighborhoods is in part shaped and defined by spatial footprint patterns. As noted earlier, spatial footprint patterns are determined by a variety of factors, most notably: physical and social distance. Physical distance stems from the first law of geography - near things are more related than distant things [220]. Social

in a neighborhood. At what frequency do people collectively organize to address neighborhood problems? Assuming this is a relatively rare occurrence even in the most cohesive neighborhoods, it raises the question of whether it is possible to actually observe different neighborhood processes.

[39] As I noted earlier, neighborhoods are also interdependent due to social ties.

distance represents the differentiation between various categories of social characteristics, including age, economic status, and race. Social distance is in line with research on social similarity to suggest socially similar areas have more homophily and are more likely attracted to each other. For example, while wealthy residents have the potential to travel to a wider range of areas with more money, they likely only actually travel to a selected range of socially similar spaces. Wealthy residents' activity patterns will likely most often be attracted and constrained within wealthy areas. This implies non-random selection patterns of people's travel behaviors, and these selection processes have consequences for interdependencies between different neighborhoods and exposure to different areas.[40]

Neighborhood research has used "spatial effects" methods to capture how processes in one neighborhood are dependent upon other nearby neighborhoods. Similar to the earlier discussion about boundaries, these approaches are explicit specifications for what it means to be "nearby". The question becomes: what does it mean to be nearby? How far and in what way? Is it a block? A mile? 2 Miles? Are these equally likely in every direction? As noted earlier, the physical and social distance between different people may help give more theoretical consideration for how the nearby area matters for different neighborhood processes [134, 219].[41] The "W matrix' is the statistical measure of the way the nearby area matters. The underlying theory for what is driving this spatial process is what is captured in "The W", but it is often given little emphasis.[42] In what follows, I discuss four issues regarding research on how the "nearby" area has an impact on a focal neighborhood area: 1.) Why would the nearby area matter? 2.) Selection as process: What is diffusing or spreading between neighborhoods?, 3.) Temporal processes - sequencing and time to spread between areas, and 4.) Urban form. I now turn to each of these issues.

*Why would the nearby area matter?* The nearby area might matter to the extent that it

[40] Although the wealthy might be aware of high crime areas, it is unlikely to be experienced as a part of daily life.

[41] Some research makes a distinction for diffusion of "benefits" or negative consequences, but explicitly what are the benefits is less clear.

[42] The majority of studies have relied on four approaches for defining "The W": queen's contiguity, rook contiguity, inverse distance, and inverse distance squared.

provides new information, exposure, and potential accessibility to more services, resources, and people. All of these things are expected to return from the nearby area in some fashion. For example, if I live near a wealthy neighborhood, this should provide a better experience in my home neighborhood regardless of the extent of wealth in the focal/home neighborhood. Over the long term, an individual's spatial footprint pattern arguably forms the probability of two or more people being in a relationship, basis of attitudes, perceptions, identity, and experiences. An individual's participation in a variety of institutions (i.e., the family, work, religion, school, peers) shapes much of daily life. The spatial distribution of when different institutions are occupied suggests variability in the availability of opportunities for success, crime, and numerous other social phenomena. While spatial footprint patterns may in fact determine the availability of institutions over longer-term patterns, on a daily scale much of this selection has already been determined. The institutions that organize individual life are linked together by people's spatial footprints.

Much of the spatial effects literature conceptualizes the nearby area as a singular process being on the same spatial temporal dimensions. However, given differences in spatial footprint patterns (e.g., work, school), different spatial footprints may not all impact the focal neighborhood in the same way. For example, if people in one neighborhood travel 2 miles to the grocery store, while people in another neighborhood travel 1 mile to the grocery store, this would suggest different conceptualizations of the "W matrix". Different nearby processes and interactions with the focal neighborhood through movement suggests different spatial conceptualizations for different variables. As discussed more in the next chapter, social distance in regards to various categories (i.e., race, income, etc.) may matter for the W matrix by influencing where and how nearby areas matter - presumably each area nearby would not matter equally and in the same way. The extent of movement and mixing patterns between neighborhoods might be one measure of the intensity of exposure between two neighborhoods.

*What is diffusing or spreading between neighborhoods?* The spatial footprint of residents is one approach for theoretically defining how the nearby area matters and more explicitly conceptualizing what is diffusing between neighborhoods. In other words, what makes two areas interdependent? In this instance, my focus is on people traveling around during their daily activities. Rather than something to be statistically controlled away, selection into different neighborhoods becomes an interesting theoretical process [191]. Selection into neighborhoods research has mostly focused on long term residential sorting processes, but these processes also unfold on a daily time scale with individual's commuting patterns.[43]

Drawing from the geography literature, spatial footprint patterns can be conceptualized as individual's activity spaces. This implies that the collectivity of these activity spaces may have an impact on the activity space of the neighborhood. While research has focused on the activity spaces of individuals, this approach does not necessarily tell us about the activity spaces of collectivities such as neighborhoods. As individual people travel around, they will not necessarily all be exposed to the same context and information. Drawing from the individual measures of an activity space, the neighborhood activity space might be represented with a variety of approaches and different types of activities:

1. Use only the home neighborhood
2. Use the locations of the activity spaces (e.g. a work location). This might vary by activity or sets of activities.
3. Add information nearby each activity (e.g., people eat lunch nearby their work if they leave the building)
4. Within residential neighborhood vs. outside residential neighborhood for different residents. For example, a higher proportion of residents participating in activities within the unit might suggest more neighborhood satisfaction and cohesion. This approach implies identification and awareness of those within vs. outside of the neighborhood.
5. Incorporate information on the paths (e.g., journey to work) to work and not just the

[43] Arguably, the long term residential sorting and daily commuting patterns are related over time. This might imply a growing city and expanding boundaries.

start/end points.

6. Convex hull, ellipse, or other spatial clustering methods. These arguably only make sense for walkable areas.

7. Potential of where go vs. actually go

*None of these approaches incorporate information on the timing of people moving between different areas.* There is implicitly expected to be instantaneous diffusion between focal and nearby area of benefits, knowledge, exposure, and a negative things. The process of how people find information (and other resources) and bring it back from the nearby area is largely unknown. It is unclear how any service or information about the nearby area is spread to others in the focal neighborhood (e.g., do residents know that a voluntary organization or business exists? Is it through media? where do they get this information?). Future research might examine this information flow by focusing on the structure of gossip between residents and other social ties.

*The urban form and the layout and city.* Neighborhoods and their effect on the nearby area are likely dependent upon the spatial landscape of the overall city. The urban form of the city may impact the way different neighborhoods are interdependent. The fit of a particular neighborhood within the overall spatial layout of the city might have an impact on the way the nearby area might matter.[44] If neighborhoods are interdependent due to people moving between them, this implies a broader and more holistic understanding of how a neighborhood relates to other neighborhoods in the city.

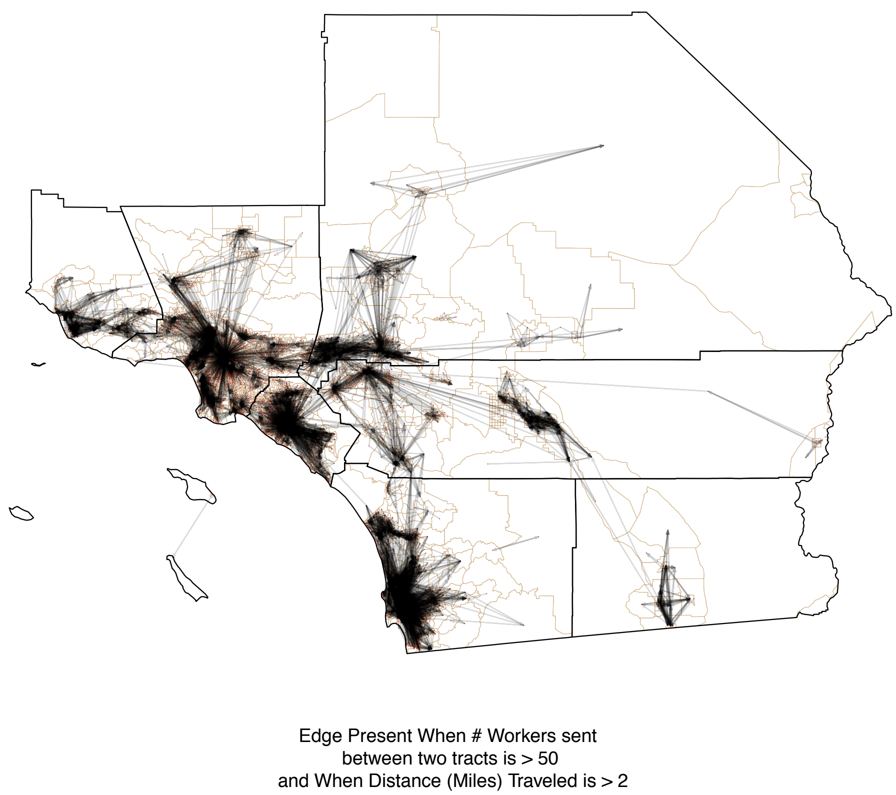
Most neighborhood research implicitly suggests that the location of a neighborhood within the broader city is irrelevant.[45] The structure of how different neighborhoods are linked together is not given much consideration. When examining work commuting patterns in Figure 2.2 for the Southern California Region (an area often expected to have challenges in commuting), we see that many people travel to different areas for work.

[44] The spatial distribution of land uses might also play a role.

[45] The use of geographically weighted regression is used to combat some of these issues, but one drawback of the approach is the lack of theory driving the process (it's a data driven technique).

People are not easily bracketed into one tract or city area, and many footprint patterns are spatially clustered. These patterns suggest that the selection of spatial footprint patterns has structure and spatial concentration.[46] Other commuting patterns such as school locations are likely even more spatially concentrated in part because of fewer opportunities to select a potential target location.

Figure 2.2: Work Commuting for Southern California




Different layouts of cities (e.g., one central downtown) likely have implications for neighborhood boundaries and processes, but this is rarely examined in neighborhood research.[47] The urban form of city is often conceptualized in a variety of approaches: concentric zones, urban villages and new urbanism, sector theory, and multiple nuclei.

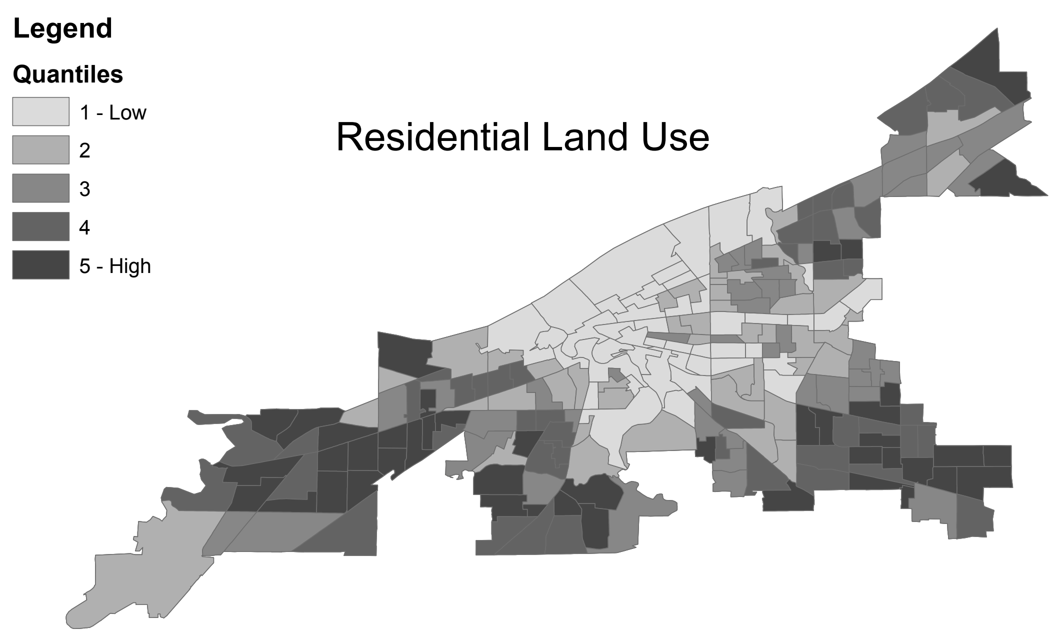
[46]This might even be conceptualized as a network with varying degrees of indegree and outdegree. Models on commuting networks are a step in this direction.

[47]A similar idea would examine regional effects and the placement of a city in regards to the density and distribution of rural area nearby (i.e., the interplay between downtown and nearby area).

Regardless of the specific conceptualization, one commonality to research in this area is that it centers around the existence of a centralized business area (i.e., centralized non-residential land uses). A concentrated urban business core suggests a particular selection pattern to people's spatial footprints, interdependencies of neighborhoods, and a broader citywide understanding to neighborhoods.

Similar to many Midwestern cities, as suggested by Figure 2.3, Cleveland Ohio has one centralized urban core.[48] The majority of residential area surrounds the outskirts of the city.[49]

Figure 2.3: Residential Land Use in Cleveland, Ohio 2005




With one defined urban core, this suggests a concentrated form of exposure and a

[48] *Appendix A* provides details for how the land use data was collected and coded.

[49] As another example, the concentric zone model suggests that different land uses of the city will be all spatially cluster in rings around a downtown center (e.g. industrial area ring), and the city will have a core and periphery structure.

broader understanding of neighborhood dynamics.[50] The spatial concentration of businesses and disorder to many downtown urban areas suggests more visible signs of disorder to a broader range of people, than just being spread out evenly over the city. Accordingly, cities with one concentrated urban core may in fact be worse off than cities with multiple urban cores because footprint patterns are likely more centralized within one core.

The location of streets and other land uses are also not evenly distributed in the city. For example, downtown areas have more intersections than more peripheral areas in the city, which would give these areas a much greater chance of having more hot spots and opportunities for crime. The concentric zone model also implies differences for different land uses. Different land uses might have consequences for the interdependencies between different neighborhoods. For example, a residential neighborhood near other residential neighborhoods may have less crime during the night presumably due to a protective effect of nearby residents. On the other hand, a residential neighborhood that is located near a commercial or industrial area would have higher crime rates due in part to being situated next to these spaces that probably have less guardianship and social control. Yet, if a residential area is nearby a vacant office space during after work hours, this suggests that some crime types may be less likely due to the lack of targets as well. Moreover, as I note later, some types of crime are likely not going to happen in some areas of the city due to the lack of people in those spaces for different times of day.

Land use in tandem with residents' spatial footprints has consequences for a neighborhood's social and spatial isolation from the rest of the city. Residents might avoid areas with vacant buildings because these unoccupied homes create fear for one's public safety [215]. This might suggest that residents would alter their spatial footprints to avoid this area. Thus, the absence of residents' spatial footprints in an area makes crime more probable through a lack of guardianship and isolation. While not specifically discussing

[50] While research has incorporated measures of distance to downtown, this does not really capture the implications of a concentrated citywide urban core or the interdependencies between different neighborhoods. It is also not explicitly clear how to determine where a downtown begins and ends in a city.

guardianship, [233] suggests that high poverty neighborhoods are plagued by higher crime rates because residents of these areas are socially and spatially isolated from jobs and the larger city. Yet we have little understanding of what it means for a neighborhood to be "isolated" [127, 132]. As one example, a neighborhood may be isolated in the sense of a lack of economic opportunities outside the neighborhood through a "spatial mismatch" where residents are located far from employment [105], or a lack of ties to elite members (e.g., political leaders) of the city [191]. Neighborhoods in other parts of the city are arguably more interdependent, while the underclass is isolated from this pattern. The spatial footprint of residents is arguably a fundamental measure of the extent of isolation of a neighborhood in comparison to the rest of the city (see also [10]).[51]

### 2.4.3 Population Density, Land use and Daily Life

One of the main consequences for spatial footprints is the change in population density of different spaces throughout the day. The sorting of different people in space and time explicitly changes the state of neighborhoods. When population shifts to different parts of the city, the population density of the area changes. These changes in population density fundamentally alter the isolation, supervision, exposure, segregation, availability of resources, and of course, people in a neighborhood. In this way, accessibility, availability, and exposure are expected to be fundamentally more fluid than often considered in the literature [126], however, there is little empirical evidence for these assertions.[52] Nonetheless, even before any *change* in population density, the city is already unevenly distributed in terms of residential population density.[53]

[51] There are several possibilities for capturing how a neighborhood is situated with other neighborhoods for the rest of the city. I've mentioned land use, social distance, and physical distance measures. Another area of research might use various network measures to capture how a neighborhood is linked to other neighborhoods. This network of neighborhoods might be done by considering degree or other centrality measures and their spatial distribution.

[52] As I show in Chapter 5, there are considerable changes in population over the day.

[53] Most often neighborhood and individual measures are only socially defined in absence of a physical world. We often examine rates of some group in a neighborhood and not densities of this group within the area. The distinction is the denominator as a total set of the population vs. an area. There is also a question of

With population changing throughout the day, the potential for different resources within the area may change. Similar to spatial footprint patterns, the patterns of the changes in population density are likely regular, nonrandom, and occur in cycles. I expect for the changes in density to oscillate in a regular stable pattern over the day, week, and season. As indicated by Figure 2.4, when people leave for work and school during the day, the population density of the home and work/school neighborhoods change.[54] When looking at the numbers of the largest quantile, we also see that many neighborhood populations are changing considerably.

Rather than just changes in population, changes in the population density suggest broader demographic changes for different groups of people and their spatial distribution over the day. Using race as an example, Ellis et al. (2004) observed that when measuring the segregation of the city using work locations, segregation levels of the city were lower [54]. Women and men are not spatially distributed equally during the day if women are more likely to work in the home [122]. While this research is informative, age, life course, and family structure of residents have not been examined in prior research. The location of different age groups is likely fragmented at different times of day. Young people are most often in schools, while elderly are likely less spatially mobile. During different points of people's life courses they will be more likely to occupy different areas of the city (e.g. young people live in more urban areas or near college campuses). Similarly, different family structures are likely not equally distributed in different areas of the city (e.g. more single people live downtown, families live in suburbs) but empirical research is needed to test these possibilities.

The changes in population density are in part a function of the distribution of different land uses in the city, and this distribution has consequences for crime. Different land uses

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measurement error in the sense that social processes are much more challenging while the physical world is arguably easier to capture. Neighborhoods as geographic and spatial entries are essentially fully exchangeable with any other neighborhood as long as we know the social attributes of them.

[54]The maps are created using data from the Longitudinal Employer Household Dynamics (LEHD). I discuss these data further in Chapter 5.

of the city situate criminal opportunities by structuring the availability of offenders, guardians, and targets [101, 109]. The fact that crime is not randomly distributed in space suggests that the uses of space (e.g., residential, retail, industrial) are critical to understanding where crime occurs (e.g. see also [12, 25, 112, 208, 213]). For example, many residents leave home and go to work as a part of their daily spatial footprint. This implies an effect for at least two particular types of land uses: *residential* for the home area and *industrial* for the work area. The change in the presence of people in each of these spaces will likely change the guardianship of these spaces at different times of day, such as less guardianship in residential areas when people leave for work.[55]

While land use and crime stems back to at least the work of Jane Jacobs (1961), the burgeoning research on land use suggests that crime of various types (typically robbery and burglary are the focus) increases when nearby convenience stores [52], large shopping centers [212], alcohol outlets [4, 66, 75, 84, 159, 163, 170, 183, 231], the city center and central business district [9, 46, 203, 208], mixed land use [25, 98], public housing [50, 72, 148, 170, 184], schools [128, 231], sexually oriented businesses [144], bus stops [137] and rapid transit stations [12, 14, 163]. A growing research area has also tested interactions between land use (e.g., retail, residential, industrial) and disadvantage [25, 213]. Most studies that focus on land use, however, only analyze one type of land use and rarely consider multiple land uses in tandem [213].[56]

[55] It could also be the case that potential offenders are sometimes guardians as well.

[56] For an exception, see Smith, Frazee and Davison (2000). This study measured several land use characteristics and examined how they related to robbery rates. Although this study provided important insights of various land use characteristics, it did not take into account the characteristics of the larger area - either social demographic or physical characteristics. As a consequence, one goal of this study is to examine these missing parts of the environment and other crime types.

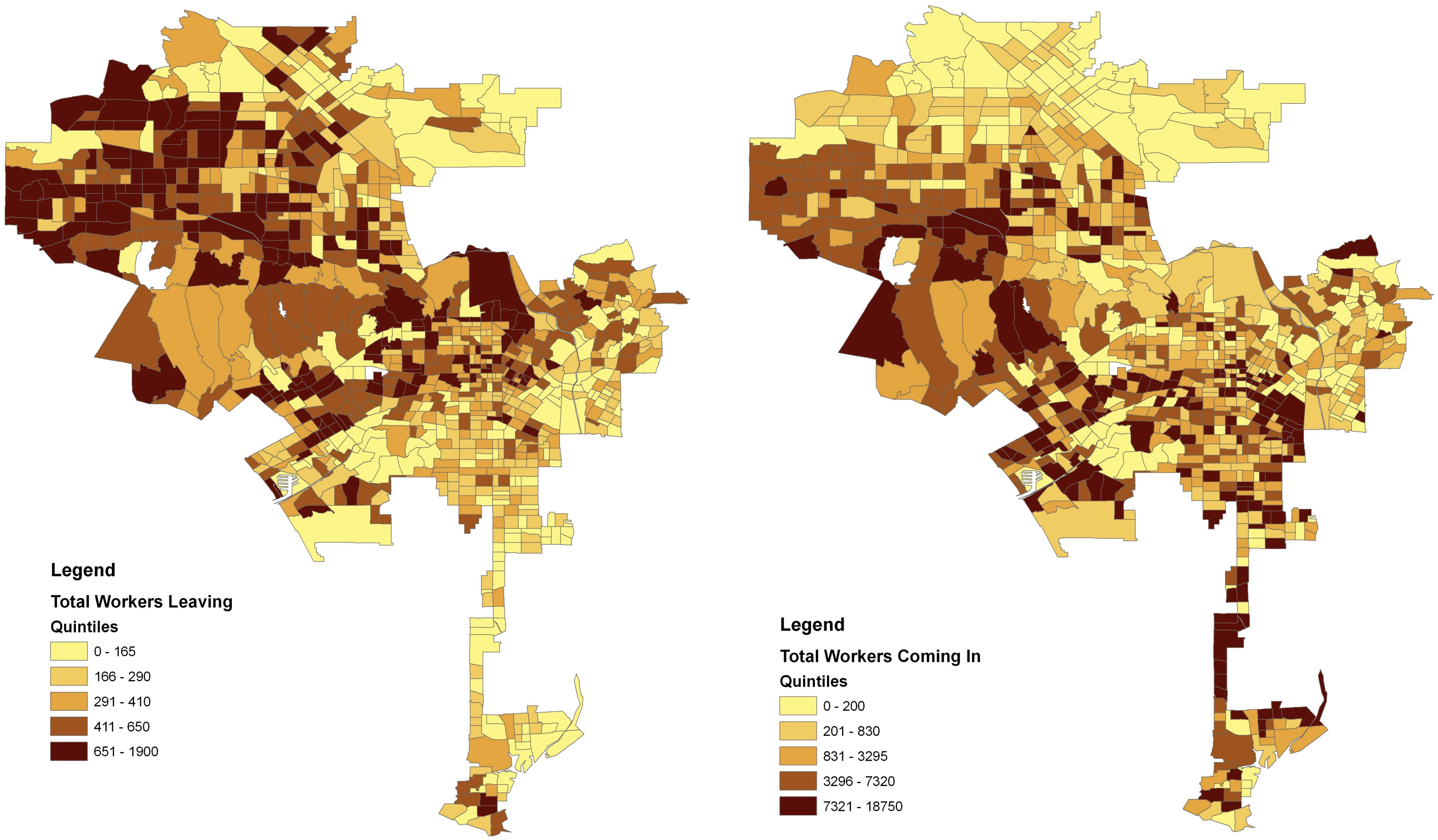



Figure 2.4: Workers in Los Angeles, 2010. The map on the left has workers *leaving* the tract during day. The map on the right shows workers *coming in* into the tract during day.

### 2.4.4 How would informal social control prevent crime?

The workhorse of social disorganization and collective efficacy theories is informal social control: a person or group's ability to intervene and actually stop a criminal event [31, 203, 222]. This definition necessarily focuses on actual social control behavior and not perceptions of social control behavior [211]. The agents of social control from social disorganization and collective efficacy are arguably the guardians, handlers, and place mangers in routine activities theory. In a sense, they would likely do the same task of stopping offending behavior [84]. Less clear about this process is how would informal social control work to actually stop a crime?

First, this question implies making a distinction between *formal* social control and *informal* social control. Formal social control can be conceptualized as laws and the police enforces these laws. The police are a scarce resource who cannot be everywhere at once (i.e., their spatial footprints are constrained by time and spread of officers), and it is unlikely they are aware of all crimes during the commission of them. They are often only contacted after a crime has already occurred, and therefore in this instance, did not play any direct social control role. The majority of social control for neighborhood research is done through informal social control and implicitly guardianship.[57] My focus is on *actual* informal social control in a neighborhood.[58] This implies it is important for people to be physically present to restrain others - not in their homes, up in buildings, it's not good enough for a parent to tell their child not to do something. Thus, the *spatial presence* of people is fundamental for social control and supervision.

Regardless of the activities of offenders or targets, a necessary requirement for informal

[57] An issue that I return in Chapter 5 is the time scale of these social control processes. Routine activities is arguably much more situational, while collective efficacy and social disorganization theory processes are much slower over years. However, even if social disorganization is slower, it still is unlikely to be completely irrelevant over daily life since it arguably sets a part of the potential for informal social control.

[58] This isn't to say that *potential* informal social control is not important, and this is an issue I will return to shortly. Moreover, we might consider larger structural processes such as the media or city resources that might matter for social control, but it isn't clear how these would necessarily be distributed at the neighborhood level. Presumably an effect from the media would saturate to the entire city.

social control is that someone is *available* to perform social control. This idea is implied in work looking at activity on the street [26, 98], as well as the changes in population density throughout the day that I noted in the last section. Assuming someone is available within a space during a particular time, their *presence* might be enough to prevent a crime, and thus the person would not necessarily need to be aware that they are performing guardianship functions.

The spatial footprints sort people into different spaces of the city during different times, and thus the availability and presence of social control and guardianship is likely crucially dependent on spatial footprint patterns. This implies that regardless of the *capability* of guardians, much of crime prevention is implied through the availability of people.[59] This suggests that availability of people is enough to control crime within the area, and there are no distinctions for different types of people or neighborhoods with different social characteristics, other than how these characteristics impact spatial footprint patterns - an issue I return to shortly.[60]

The presence of a person in a space during a criminal event may not be enough to prevent the crime. Assuming at least one person is available, the person needs to be *aware, willing, and capable* to perform actual social control [182].[61] How could we identify (i.e., become aware) of someone committing a crime? While not examining social control behavior in action, a survey of residents in The Hague suggests that offenders are not identifiable by appearance (i.e., clothes, race), but in fact by their behavior (e.g., using

[59]The guardianship process is also likely not constrained to one individual. As I note later, different availability patterns also suggest different crime patterns, and some crimes may be more or less preventable by people's presence while other crimes are more attractive with more people around.

[60]More complicated approaches might suggest that availability is not enough, and the types of people available and their social networks may play a role [168, 218, 87].

[61]Much of the theory for this step of informal social control is implicitly based on research in social and developmental psychology on how parents supervise their children. In this case, the focus is on how parents become aware of children doing deviant behavior. Psychology research suggests that parent's *knowledge*, *attitudes*, and *effort* in regards to their children's behavior is critical for a variety of outcomes (e.g., whether children abuse substances [136]. The knowledge, attitudes, and effort from psychology seem largely consistent with the social control processes of awareness, willingness, and capability from Reynald's work. Similarly, Sampson et al. (1997) note that their model of collective efficacy is based on Bandura's model of self efficacy [188]. Much of this insight in regards to awareness also implicitly comes from psychological work on *situational awareness* [56].

drugs and/or acting secret) [180]. How this process turns out for actual crime in neighborhoods remains uncertain. I would suspect the process is quite challenging given how fast may crimes are committed, and people would still need to be fully aware and observant. Some crimes also have more visibility on the street, while others are often indoors. Similarly, while due in part to crime type differences, it is not necessarily straightforward how to identify when someone is an offender or victim.[62] If they can't be identified before a crime happens, this makes the categories of "guardian", "offender", and "target" even more challenging to identify. How would a person be able to determine whether a crime is occurring vs. something else or even at all?

Assuming a person is aware a crime is about to occur, the next step would be to decide if they are *willing* to intervene to actually stop a crime. Research in this area suggests that more wealthy areas are more likely to indirectly intervene in a crime by calling the police [180]. Nonetheless, there are several other potential factors that have been shown in the literature [181]: collective efficacy, fear of crime, social distance, severity of sanction, time of day, physical size, physical availability, to name a few. All of these factors suggest different variations for whether or not someone is willing to perform actual social control.[63] Nonetheless, many of these factors may be context specific and might vary as a function of space and time. For example, when discussing the process of informal social control, there is often an implicit conceptualization of a spatially and temporally static guardian or agent of control. Much of the work is conceptualized from the perspective of someone performing social control in front of their own home or reporting whether their neighbor would perform social control (e.g., break up a fight at neighbor's home in the collective efficacy measure). At the same time, research on social ties in neighborhoods have been challenged for people's unwillingness to intervene when they have a tie to a delinquent's parent or

[62] This process is arguably impacted by cognitive biases, memory, and our perceptions for expectations for criminal events.

[63] St. Jean (2007) also suggests that the history of interaction between groups may be important when deciding whether or not to intervene. When examining St. Jean's work, it appears that residents rarely willing to get involved because they were fearful of retaliation [101].

grandmother [23, 168]. One commonality to this research is that it is arguably based in part on how people feel about supervising other people's children. Given that young people commit most crime, this might be an important area for future research since informal social control implies acting on someone else's child.[64]

The variety and structure to spatial footprint patterns suggests a certain degree of regularity into the availability of guardians across neighborhoods, but less clear is whether people would always behave the same when *outside* of their home neighborhood. Rather than a focus on the processes of residents who live within an area, people may behave differently when outside of their focal neighborhood, and the factors for crime control may play out differently.[65] This possibility is largely absent from criminology and neighborhood research. It is unclear how people from outside the neighborhood would feel about intervening in a problem that is outside of their home neighborhood, or with someone of greater social distance.[66] There are several possible scenarios for how this might play out:

1. It does not matter if you are within/outside of your neighborhood. If you are willing to intervene then always willing.
2. You may be willing to intervene if it's just nearby your neighborhood.
3. Only intervene when little social distance. This may or may not occur outside the neighborhood.
4. Another approach might suggest that people are willing to intervene to the extent they know others in the area. This might be most common in areas where people visit regularly or with some sense of attachment. In this case, a work area may be one such place, but not another place that is less visited.

This distinction of inside vs. outside of the neighborhood is dependent in part of a person's ability to identify in some capacity the membership of the neighborhood or area,

[64]This implies that research needs to more explicit consider the relationships between victims, offenders, and guardians.

[65]It also may be the case that local residents are not the population that we wish to capture. In other words, the residential population of an area may not be the most salient.

[66]Many residents may not feel comfortable directly intervening, and might resort an indirect approach (i.e. telling another child's parent, calling the police)

which may not be reasonable or mutually agreed upon. What percent of your neighbors do people know on average? How about when a person is located in other neighborhoods? The change from within the home neighborhood to outside of the neighborhood suggests a substantial change in the potential for knowing other people. The denominator for the number of people known is not just a Census tract, which is already large with an average of around 4500 people, but all others outside of the neighborhood (would this be the rest of the city? The county? The state?). It would thus seem likely that the percent of residents' known would be quite small, particularly outside of the neighborhood. As a result, most of the time it will be unclear whether someone actually is from the neighborhood or not. If people only intervened with folks they knew or felt familiar, this would make informal social control all the more rare and less likely.

Assuming the person is aware and willing to intervene, the question then arguably becomes about a person's *ability and capability* to intervene. The person may have in fact decided they were unwilling and thus they do not intervene. They could actually try to stop the behavior, assuming they have the ability to step in and disrupt the situation. People may have the ability and capability to step in, but they may not because they are too busy too stop, the crime is too minor, they think someone else will step in (bystander effect), or they are too far away.

The prior discussion suggests some degree of regularity with which people actually perform a social control function, and this is likely unrealistic. Crime is a rare event, relatively easy to commit, and it does not take much time.[67] The opportunity to actually perform social control is likely an even rarer event, particularly for some crime types. This makes it quite challenging to actually measure, and thus a focus on the *availability* of potential people for social control might be a reasonable first step then trying to observe more complicated social processes. Using an approach with a spatial footprint in mind, we

[67]It may be important to know how rare a crime event is for a neighborhood. While some neighborhoods have more crime than others, it is unclear whether people actually see more serious crimes in action. If not, it is unclear how social control might operate for serious crime.

might more appropriately characterize the fluidity of social context for understanding everyday crime patterns (or lack of patterns given the rarity of the event).

### 2.4.5 Different types of crime and different spatial footprints

This section focuses on crime. What is it? Where is it? When is it? In what follows, I briefly mention several general findings and ongoing debates within criminology about crime. In what emerges, I discuss how different spatial footprint patterns are related to different crime patterns.

*What is crime?* An ongoing debate in criminology is how to define the dependent variable. The issues are around defining crime legally, deviant behavior more generally, and/or as a pathology. Another related issue is whether crime should be self-reported, victimization reports, or arrests from police (e.g. see [81]). In my dissertation, I use crime data from police departments, and I focus on serious part 1 crimes: robbery, burglary, assault, motor theft, homicide, and larceny. In Appendix A, I discuss the crime data collection and coding more completely. These data are likely an underreport of the true measure of criminal activity in the city in part because not all crime is caught or reported as seen in victimization reports. The underreporting and undercounting of crime (i.e., the "dark figure" of crime) is less likely an issue for more serious offenses than less serious crimes though. Serious crime is an extremely rare event. Given that serious crime is extremely rare, it may be more reasonable to examine where and when crime occurs - criminal events - rather than trying to distinctly define why a person commits a crime in some scenario and not in others.

Different types of crime suggest different processes in part because they often occur at different times and in different spaces. The distinction for different types of crime is most often made between violent or property crimes (i.e., whether a crime has a victim or not). Homicide is often argued to be a distinct crime type because the victim and offender often know each other, and there are often several differences among types of homicides [118]. Different types of crime suggest differences in the patterns by which spatial footprint patterns colocate people within space and time, as well as different processes all together.

As one example, consider a robbery. A robbery occurs when someone steals property from another person through force or fear of force. A robbery is essentially a violent larceny. One example is a mugging. Robberies and muggings most often occur for cash money - often for drugs [97]. Muggings are most likely to occur at night on the street in retail areas. As suggested by the 2010 Uniform Crime Reports, robberies occur on the: street (e.g., near an ATM) (43.2%), at home (17.3%), commercial (13.2%), gas station/convenience store (7.5%), banks (2.2%), and other (16.6%).[68] Most often this crime occurs after 10 pm, and it is slightly more common on weekends. Usually the victim does not know the person committing the robbery, and the victim is often vulnerable: students, strangers, drunk, and tourists [1]. As suggested earlier, different groups of people are situated in different spaces of the city at different times. Nonetheless, robbery victims are spatially and temporally situated differently. This suggests distinctions in their spatial footprints: students after school, elderly people during the day, strangers at night. One takeaway from these findings is that they suggest very little about the criminal event themselves (i.e., how someone committed a bank robbery), but they do offer insight into the spatial temporal circumstances of crime and how these patterns relate to the distribution of individual's spatial footprints. This description also gives insight into what is *not* occurring. Robberies do not often happen during the day, and most of the time robberies do not occur because they are rare events.[69]

*When is crime happening?* The neighborhoods and crime literature routinely focuses on

[68] According to the the UCR website, "other" represents miscellaneous robberies, but it is unclear what is included in this category.

[69] Burglaries follow a different pattern. Often the victim is known in some capacity, such as someone who provided as service (i.e., a plumber) [177]. This might suggest that the person has little social distance in regards to income and race. Burglaries often occur in the summer months and during the day when people leave for work. Approximately 75% occur in homes. Nonetheless, we might also make sub category distinctions such as different types of burglaries.

long term crime patterns. Most often researchers use snapshots of crime over decades or years. This implies that the opportunity over the day is constant and ignores seasonal patterns. While seasonality patterns have long been explored in urban research, particularly for crime, less clear is the theoretical underpinnings for why seasonality patterns often have strong and consistent effects on behavior and rates of crime [145, 85].

Typically seasonality refers to processes over months (i.e. different seasons), and to demonstrate this idea, I focus on Chicago and Los Angeles. I chose these two cities because both of these cities are common in the neighborhoods literature, particularly Chicago, and both are major urban areas. But, these cities have different weather patterns and demographic compositions. As Figure 2.5 indicates, Chicago's violent crime displays a clear seasonality pattern with the summer months having the most violent crime. In Figure 2.6, Los Angeles' violent crime occurs on the weekends, but there is also what appears to be a slight tendency for the summer months. Los Angeles also appears to have a concentration of data on New Year's day in 2002. This might indicate crime around holidays or other regularly timed large public events (e.g. sports events - Rose Bowl). While the composition and weather patterns are quite different between these two cities, this pattern suggests a classic seasonality finding.

The effects of seasonality are arguably capturing patterns of changes in the weather. These changes in weather and seasonality suggest changes in people's spatial footprints. On a monthly and seasonal time scale, crime may change with the temperature (e.g., when children are in school (i.e. not summer months)). But, on a day of week or daily time scale, the seasonality pattern is arguably due mostly to changes in spatial footprint patterns since weather does not change much during the day.[70] The locations of the targets, offenders, and guardians likely shift to different spaces during different times because of their different

[70] According to the American Time Use Survey, people age 25-44 spend approximately a 8 hours of their day sleeping, 8 hours at work, 2.6 hours for leisure, 1.1 hours for eating, and 3.8 hours caring for others, household activities, and other tasks. While these are "averages" of how a large proportion of the population spends its time, future research might connect these patterns to changes in crime over the day. These distributions offer some insight into the potential for social control of different neighborhoods.

spatial footprint patterns.[71]

These patterns are suggestive of different neighborhood characteristics operating differently over the day. The changes in these daily patterns are likely due in part to spatial footprint patterns and the changes in population density of the area. Many neighborhood characteristics are unclear for how they might operate over the day [153]. As a few examples drawing from Cohen and Felson (1979), more unemployed people may indicate more potential offenders and strain, which is suggestive of a process of more crime. On the other hand, more unemployment might suggest that there is less cash in the area, and thus less targets and thus lower crime. More unemployment could also indicate less guardianship in retail spaces because people have less cash to spend money and thus they are less likely to be out and about. More unemployment might suggest more availability in guardianship around the home. This pattern suggests a multitude of different findings and factors to say the least, but very little empirical work actually examines the changes in these patterns over the day. We have considerable information about how we might expect long-term crime trends to operate in cities (e.g., residential instability), but it is less clear how these factors operate on a daily time scale. As a first step in unpacking how different neighborhood factors might operate at different times of day, in Table 2.1, I have indicated the expected direction of the effect (i.e., positive, negative, or indeterminate) of a neighborhood characteristic for social disorganization theory and routine activities theory. For social disorganization theory, it is less clear what it would have to say about daytime crime since daytime patterns were not really the focus of the theory. But as noted earlier, these longer-term residential patterns might have an impact on daily behavior.

[71] Research might also examine how different seasonality patterns of spatial footprints impact the potential for different areas to collectively organize to address problems in their neighborhood.

Figure 2.5: Chicago Crime Calendar

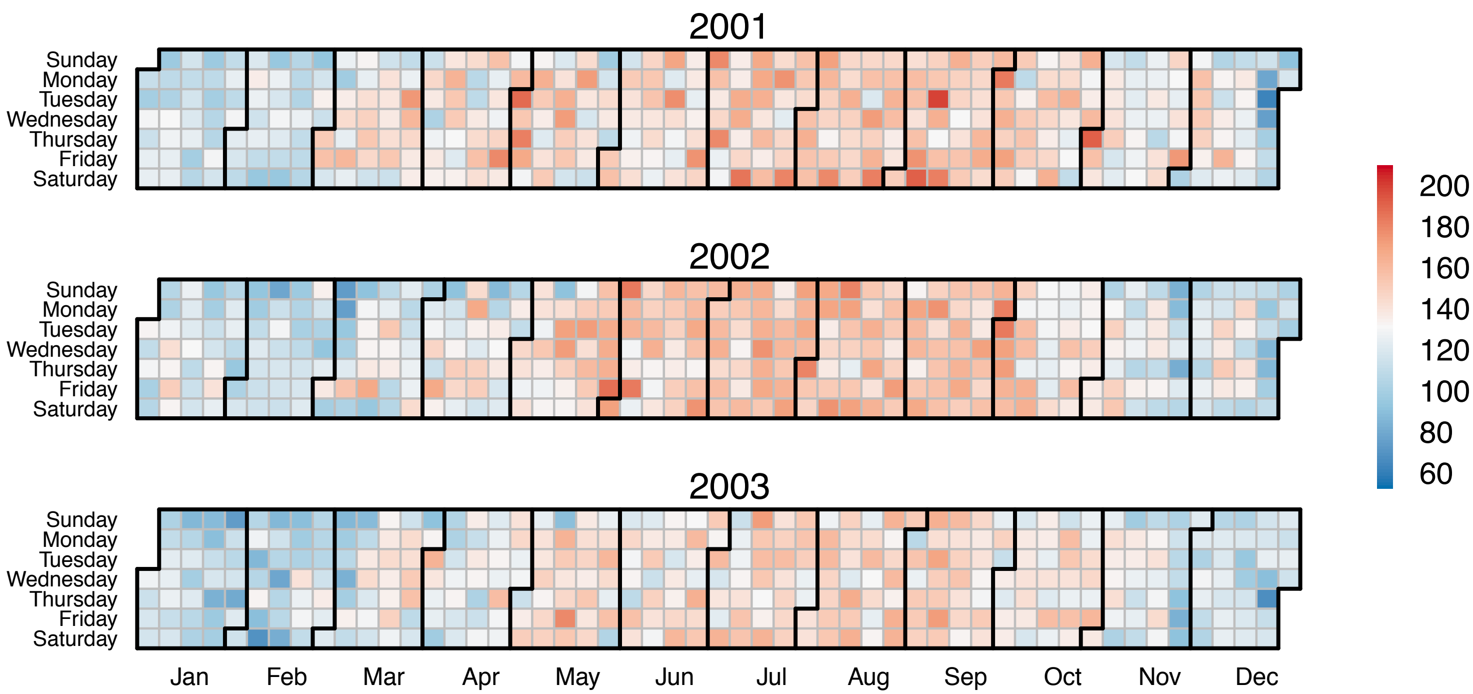


Figure 2.6: Los Angeles Crime Calendar

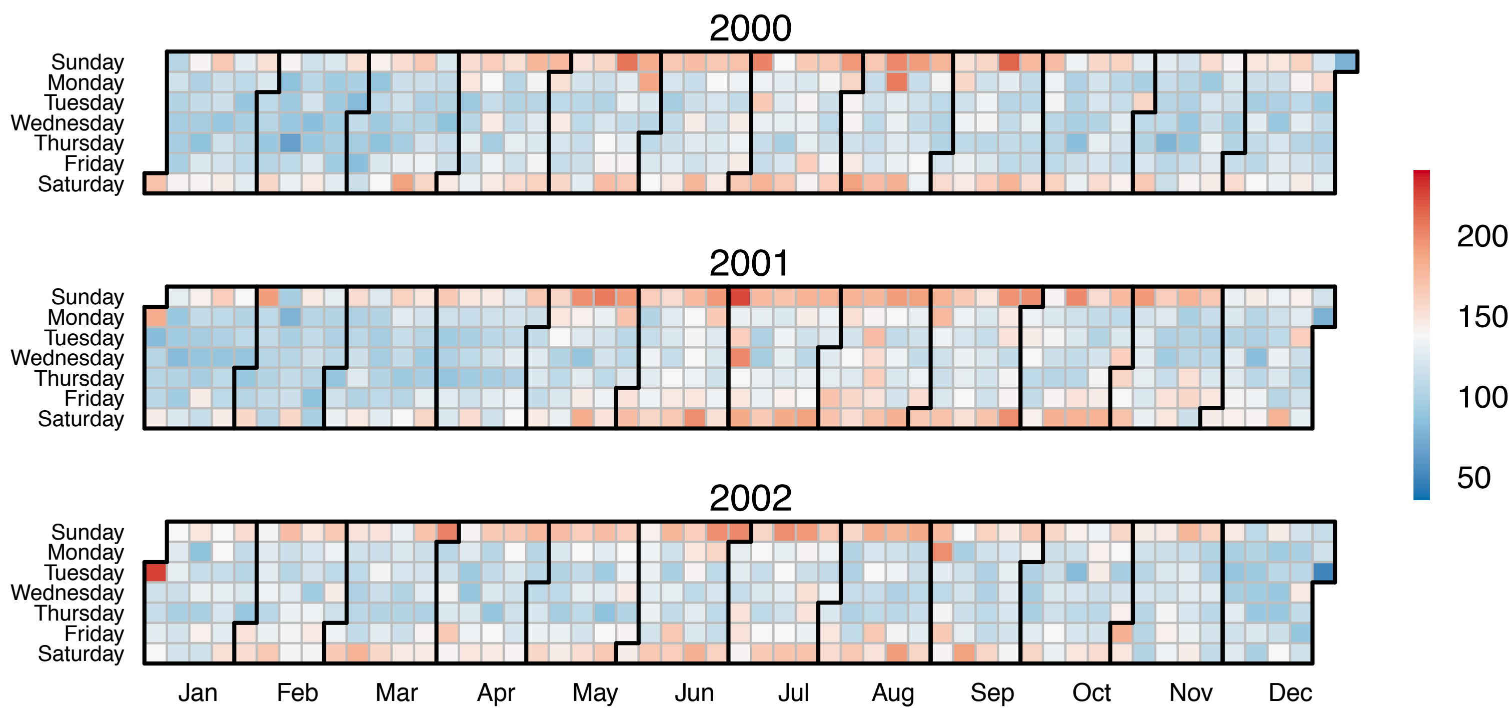


Table 2.1: Expected impact on crime by theory and time of day

| | Social Dis.<br>IND.<br>IND. | RAT<br>Day<br>Guardians | RAT<br>Day<br>Targets | RAT<br>Day<br>Offenders | RAT<br>After School<br>Guardians | RAT<br>After School<br>Targets | RAT<br>After School<br>Offenders | RAT<br>Night<br>Guardians | RAT<br>Night<br>Targets | RAT<br>Night<br>Offenders |
|---|---|---|---|---|---|---|---|---|---|---|
| Homeowners | - | IND. or - | + | IND. | IND. or - | + | IND. | - | + | IND. |
| Vacant Units | IND. | + | IND. | + | + | IND. | + | + | IND. | + |
| Population | - | - | + | + | - | + | + | - | + | + |
| Young People | + | IND. | IND. | + | IND. | IND. | + | IND. | IND. | + |
| Ethnic Hetero. | + | IND. | - | IND. | IND. | - | IND. | IND. | - | IND. |
| Poverty | + | + or - | - | + | + or - | - | + | + or - | - | + |
| Churches | - | - | IND. | IND. | - | IND. | + | + | IND. | IND. |
| Bars | - | - | IND. | IND. | - | IND. | IND. | - | + | + |
| Restaurants | - | - | + | IND. | IND | IND. | IND. | + | - | IND |
| Grocery Store | - | - | + | IND. | - | + | + | + | + | + |
| Residential LU | - | - | + | IND. | - | + | + | - | + | + |
| Retail LU | - | - | + | IND. | - | + | IND. | + | + | + |
| Industrial LU | + | - | + | IND. | - | + | IND. | + | + | IND. |
| School LU | IND. | - | + | + | - | + | + | + | - | - |
| Office LU | IND. | - | + | IND. | - | + | IND. | + | - | IND. |

*Note:* Social Dis. = social disorganization theory; RAT = routine activities theory; LU = land use; IND. = indeterminate effect from theory. As an example for the first cell, the table can be interpreted as more homeowners reduce crime, even after controlling for the other effects in the column. This table obviously oversimplifies all of these processes and theories. To save space, no distinction was made for different types of crimes (i.e., violent, property, etc.), other variables and processes, spatial scale, units of analysis, change between categories, or time scale - these processes would necessarily flip some of the signs in the table. All effects are assumed to be linear for social disorganization, while routine activities theory would suggest nonlinear effects in some instances. The activation mechanisms for all theories are unclear, including when ties activated to control crime, suitability of targets and guardians, and motivation for offenders. People may also be in more than one category (e.g., offenders can be both targets and offenders).

While the calendar figures (Figures 2.5 and 2.6) are helpful for seasonality, they mask potential variability in crimes over the day. As Figure 2.7 indicates, most violent crime appears in the evening hours. When unpacking different types of crimes in Figures 2.8, 2.9, 2.10, and 2.11, we see that robberies occur at night, assaults are after school, homicide does not have a clear temporal pattern, and burglaries most often occur during the day. As these figures indicate, crime varies over time, and therefore the explanations for crime also likely vary over time. These patterns suggest distinct changes in opportunity for crime and changes in spatial footprint patterns. The spatial footprint patterns of when different crimes are occurring over the day suggest spatial patterns for where people are located.

These temporal patterns also help to motivate approaches in criminology that are concerned with criminal events and crime rates, rather than individual decision making. If crime were only a function of an individual decision maker, we would not likely see these same temporal patterns. This structure is evidence of overall general shifts in the propensity for crime over time and space that is not likely a function of individual decision makers, but population changes at different hours of the day.

Figure 2.7: Chicago Violent Crime: DOW and Hour

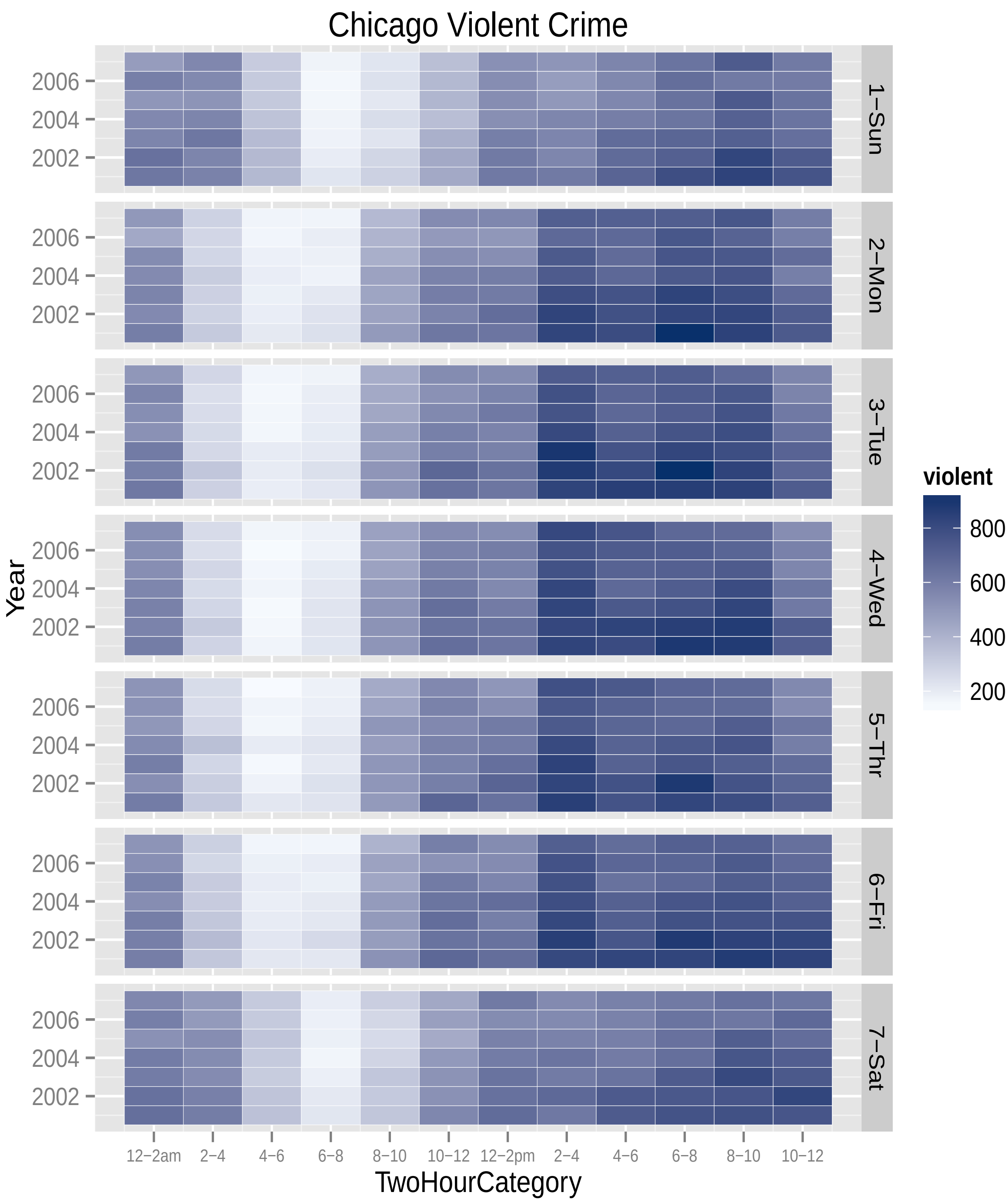


Figure 2.8: Chicago Robbery: DOW and Hour

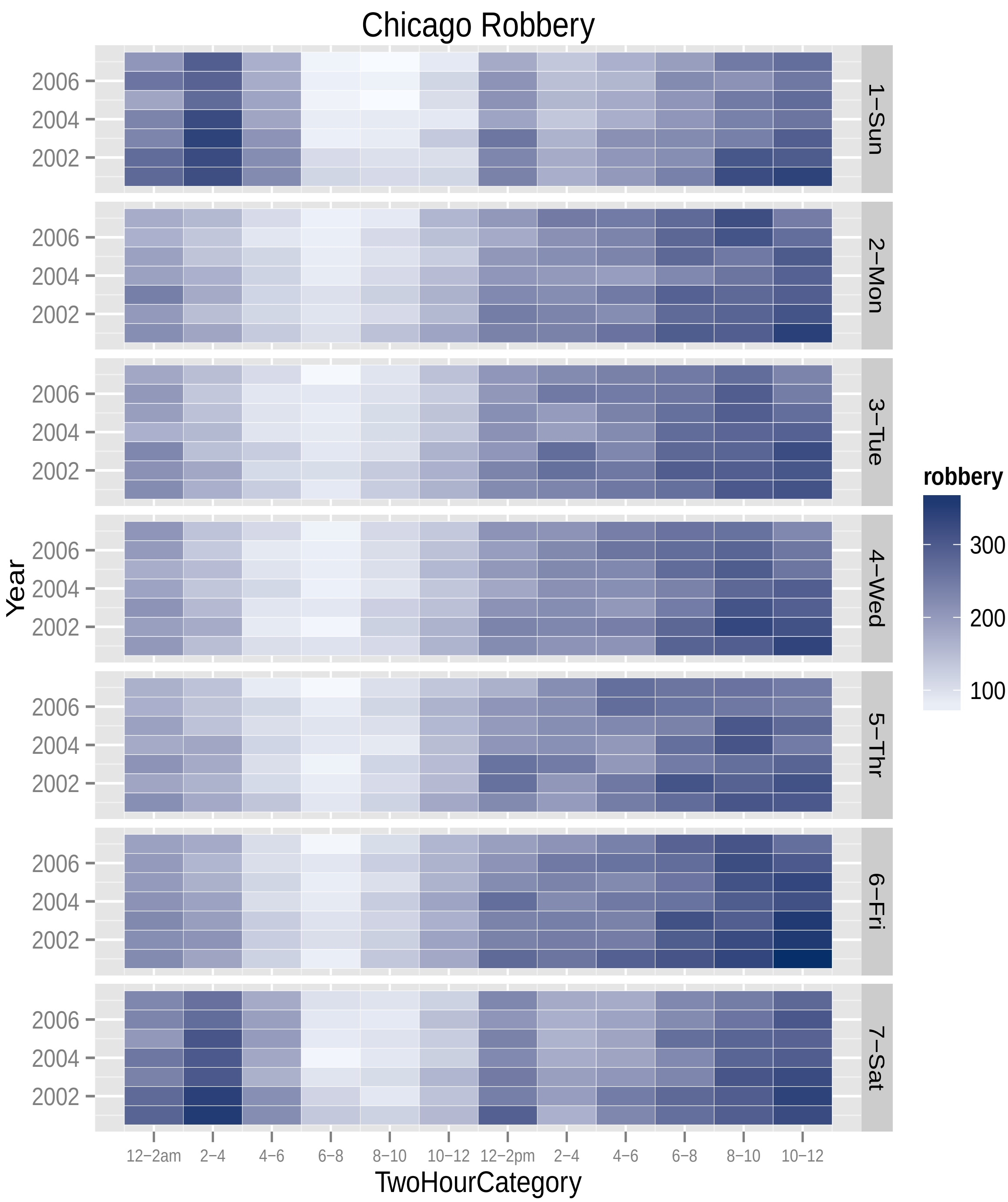


Figure 2.9: Chicago Assault: DOW and Hour

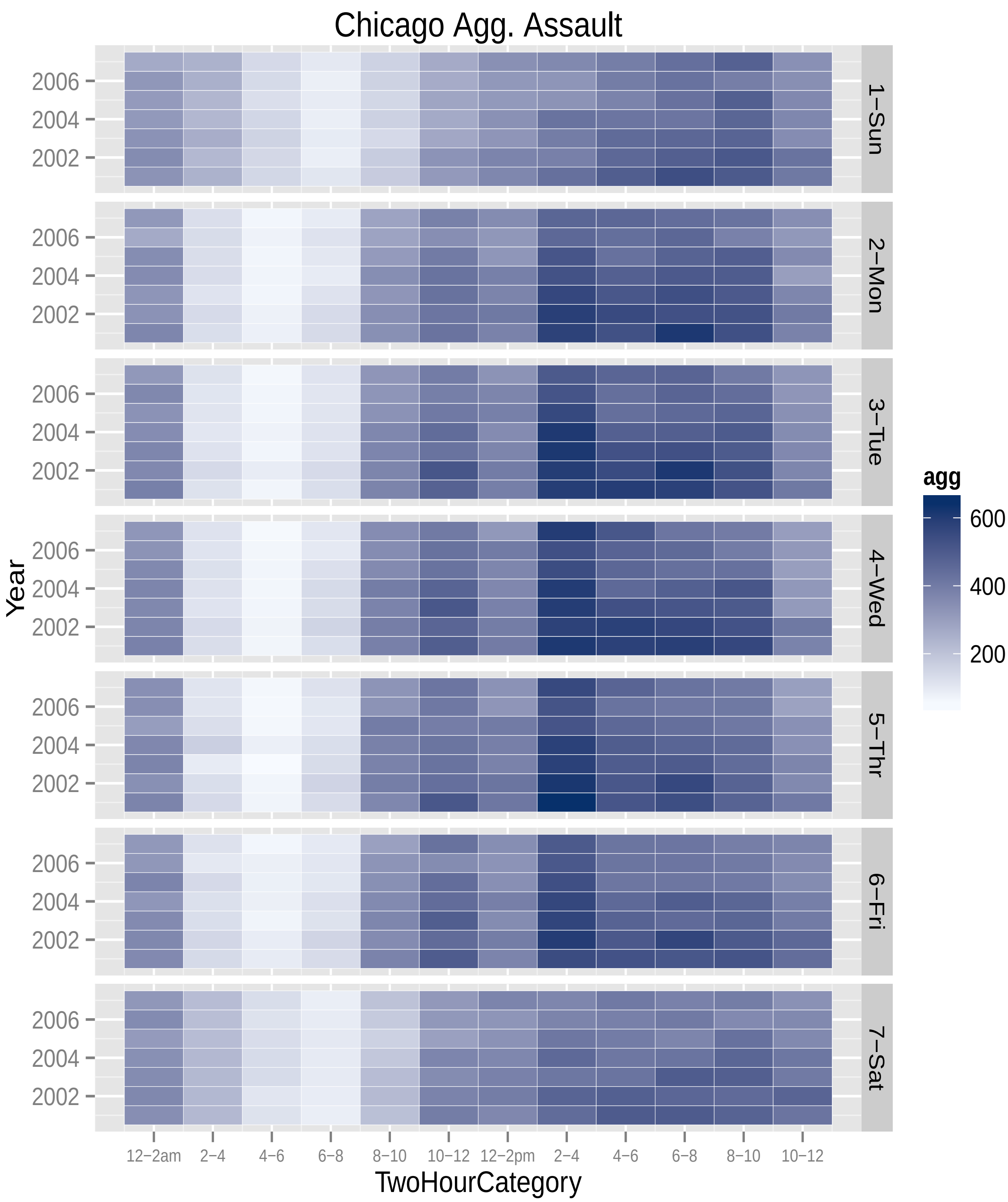


Figure 2.10: Chicago Assault: DOW and Hour

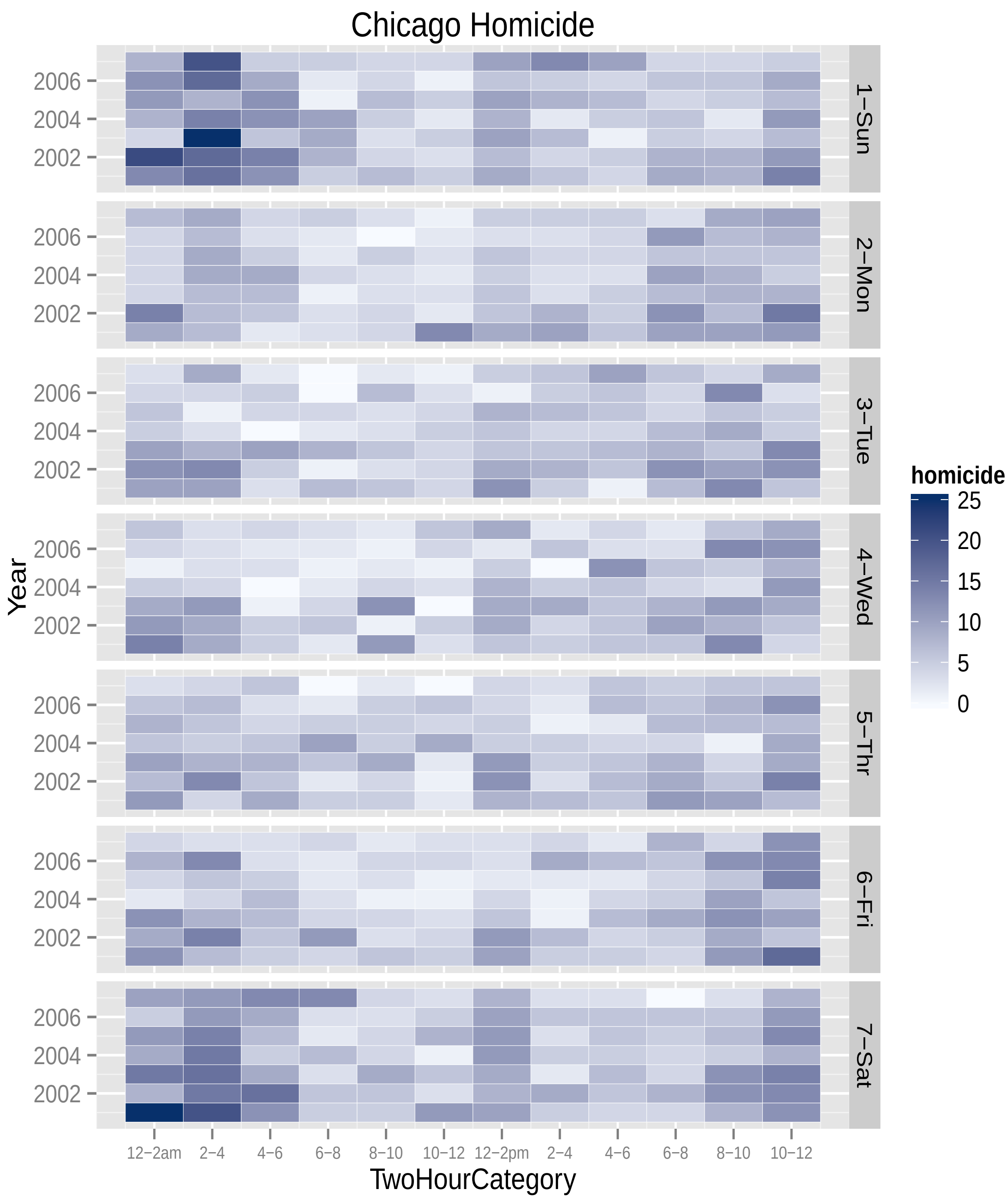
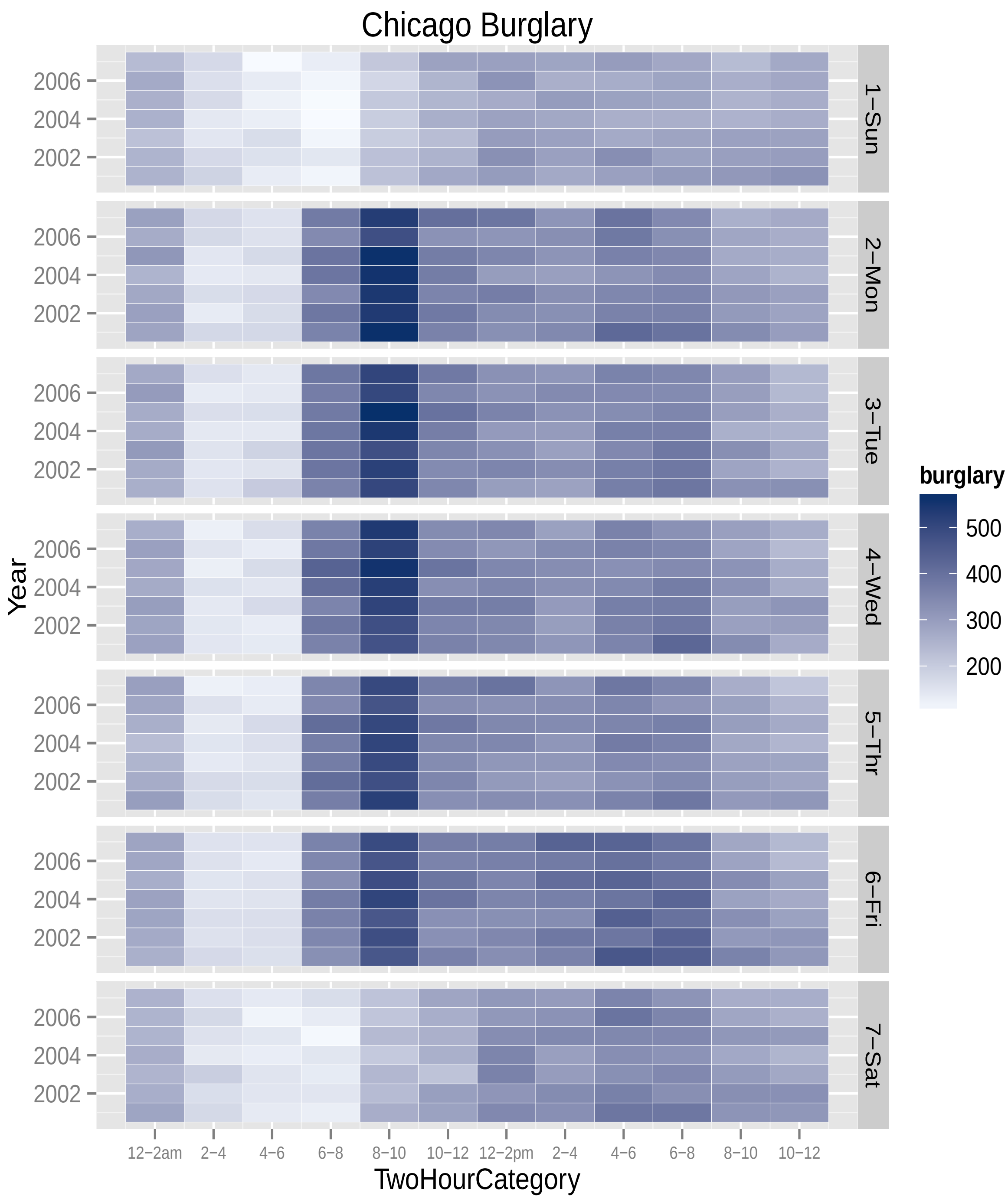


Figure 2.11: Chicago Burglary DOW and Hour



*Where is crime happening?* Research on where crime occurs often focuses on the clustering of crime in different areas, points on a map, or the rate of crime in a neighborhood.[72] When crime rates are computed, most often the denominator is the residential population of some area (i.e. a Census tract). Research has suggested the for some types of crimes - burglary and motor vehicle theft - it may be more appropriate to use the number of housing units or vehicles per area [18]. One complication for these patterns is that the population of many parts of cities is not constant over time due to spatial footprint patterns. When looking at patterns of crime over the day, the denominator of the crime rate should change as well (i.e., # of people, # of cars), but this possibility is rarely considered in prior research. It is unclear how these shifts in the population change the spatial distribution of the crime rate in the city.[73]

With these challenges in mind, it might be desirable for future research to shift attention to crime events, rather than rates of crime per population. One challenge for work on crime events is that the area where a crime event occurs can be a much wider area than one particular point on a map. For instance, a car is stolen from one area, found in another area, the victim lives in one area, and the offender was arrested in another area.[74] This pattern creates spatial uncertainty and measurement error for understanding different crime problems. When approaching crime using traditional neighborhood based approaches (e.g., within one neighborhood), it gets immediately unclear what neighborhood is important for understanding this crime pattern. With different measurement techniques of people's spatial footprints, we might begin to unpack the interrelationship between these different locations of the crime process.

One common insight from crime and place research is that different types of crimes are

[72] The majority of our understanding of where crime occurs is in cities. While more crime does occur in major cities, smaller police departments, rural areas, and municipalities are often not a part of crime of place research (for an exception see [133]).

[73] Research might also use crime per area.

[74] A similar argument might be made for a fight at a bar. What spatial environment is important for this process? Is it the home locations of the people fighting? The location of the bar? Somewhere nearby the bar (e.g., when the assault might carry over from the bar)?

more likely to occur in some spaces rather than others. In fact, the literature on crime hot spots, journey to crime, and other research on crime and place suggest spatial clustering of criminal activity [205, 224]. The debate arises around why this spatial clustering occurs? In other words, how do hot spots develop? Research from Pittsburgh has also shown that where gangs hang out, in other words their "set spaces", are formed in high density, poor minority neighborhoods [217], but we have little understanding of how these set spaces form.[75] This raises a question: how can we determine the size of a crime hot spot? While there is no mutually agreed upon technique, most often research in this area is data driven by prior crime arrests. In what follows, I briefly discuss more theoretically guided approaches.[76] They are discussed independently, but they might be better in combination.

The land uses and their spatial distribution might be used to estimate the area of a crime hot spot. At face value, this has to be true for some crimes. Bank robberies have to occur in banks and accordingly retail areas. But, when considering the spatial distribution of different areas of the city, retail spaces are often relatively spatially concentrated. In this way, the spatial concentration of land uses may implicitly make some crime more attractive to some areas, while other land uses may be crime generators, and other areas little to no effect on crime at all. Different parts of the city are at a greater risk for crime because of the spatial location of different land uses and other physical aspects, including street connectivity and urban form (i.e. is there a centralized downtown).

Another approach would use the characteristics of the residential population. This approach stems from classic criminology arguments of place, and it suggests that crime is situated by a variety of demographic characteristics, including poverty, residential instability, and ethnic heterogeneity. With these approaches, it is suggested that due to the spatial clustering of disadvantage, these areas should have more crime.

Another approach would use the spatial footprint of police to estimate the size of a hot

[75] Using the spatial footprint of gang members, the sizes of these areas could be estimated.

[76] None of these arguments take into account the temporal aspects of where crime occurs. As the previous section indicated, crimes occur at different times of day, and this suggests changes in the how long a particular area will have more or less crime.

spot.[77] The size of a hot spot might be determined by police presence (i.e., duration in a particular space).[78] This issue is similar to the issue in police research for determining where police should patrol around a neighborhood.[79] The impact of patrol decisions on offenders, residents' perceptions of crime, or crime itself is generally not well understood. For example, we have little insight on the area of impact of a police car. In other words, what is the deterrent effect to crime with police presence within a neighborhood?[80] How long does this suppressing impact maintain after this police care leaves? Regardless, the police are a limited resource where there are simply not enough of them to cover all areas at all times. Given this aspect, the police's spatial footprint and implicitly their size of a hot spot may be quite micro, although this is not necessarily problematic given the spatial clustering of crime.

Finally, building on the work of Short et al [207, 206] that suggests hot spots vary over time, we might use various spatial footprints to estimate the size of a hot spot. There are a variety of different potential spatial footprint approaches. One approach would focus on the patterns of where young people - the prime age of offenders - live in relation to their school. Another approach might use where people live in relation to where people work to estimate the potential spread of guardianship. Another approach would use journey to crime information (i.e., footprint from home to crime incident location). Yet another approach would use the walkability of different neighborhoods, and their relation to crime generating locations (i.e., bars).

[77] The size of the hot spot might also be determined through the calls for service from residents. Using the spatial distribution of calls, a spatial hot spot area might be formed.

[78] Another approach might use the spatial clustering of proactive police arrests. The area of the footprint of the prior year's crime data would likely be a good estimate for the current year.

[79] For example, should police travel 1 block? 2 blocks? Stay in one area? Move around randomly? Uniformly? Where the most crime was yesterday? Last week? Their footprint may vary by city, police districts within cities, and different shifts (e.g. day vs. night) within districts. Future research might test this possibility by including GPS devices on police cars.

[80] At the same time, much of the policing work is explicitly only focused on police activities. For example, one approach for work on hot spots suggest police deter crime through their presence. One extension to this line of work would consider spatial footprints of everyday citizens.

## 2.5 Discussion

This chapter and dissertation centers on one simple (but not duly appreciated) insight: people exist in space and time, and they move around. One purpose of this chapter was to recognize that this starkly simple insight has considerable implications for the way we approach social science and more broadly conceptualize various social phenomena. My focus on space and time is on the one hand a methodological critique, but more importantly, a conceptual argument to incorporate space and time more explicitly into neighborhood research. Approaching social phenomena with the spatial footprint in mind allows for conceptualizing how processes unfold over the day, week, and season in space. It necessarily focuses on *process* and explicitly contextualizing theory as not only changing over time, but also space. It is an approach to incorporating space and time into theory. In this way, the spatial footprint approach is not a broad theory, but in fact one way of explicitly incorporating process into various theories.

The challenges discussed in this chapter touched on a range of issues regarding time, space, and interdependence between different units. While my focus is on neighborhood crime research, these challenges are evident in many areas of social science research. Much of social science research does incorporate space into their process of interest. Just as much of social science research often tests or demonstrates how some social process is different for some particular person or demographic group, the next step is to consider the implications of social processes within space and time. The spatial footprint approach is one way to start conceptualizing these processes.

What's next? On the one hand, this chapter has set out several testable hypotheses for the neighborhoods and crime literature. On the other hand, the scope of this particular chapter of my dissertation is quite broad and not everything can reasonably be tested in the short-term. Much of this chapter is a basis for future work. That said, in what follows in the next chapter, I take a first step by examining the characteristics that explain the selection patterns of individual's spatial footprints. I focus on how choice of grocery store, work, school, and church is determined by the social and physical characteristics of place.

# Chapter 3

# Where are residents' spatial footprints?

## 3.1 Introduction

Geographers have long been interested in the *accessibility* of different spaces and individuals' path locations. At the same time, location-based data (i.e., mobile phone data) is increasingly used to track human mobility patterns over the day. Research in a variety of fields such as demography, sociology, psychology, engineering, and computer science has started to use individual's mobile phone GPS data to capture human mobility patterns for a variety of topics, including home and work commuting, social media, tourist movements, health, residential segregation, and traffic [34, 35, 49, 113, 96, 139, 175, 176, 209, 65]. One challenge for this literature is that only the "destination location" or where people end up is observed. The selection decision related to why people go where they go is lost in the analysis. In this way, *selection* is not a statistical nuisance to be explained away, but an interesting theoretical process in itself [191]. This underlies a need to understand spatial footprint patterns, the characteristics of where people decide to go out of a range of different activity locations, and the selection process by which some areas are more or less accessible. This raises a question: What factors are important when deciding where people choose go?

Although there is a dearth of empirical work in this area, the geography literature does provide a bit of theoretical guidance for this question [64, 111, 92, 99]. The space where an activity takes place is expected to play a major role in the choice of spatial footprint patterns. Four main and interrelated factors are expected to contribute to where residents choose to travel for their spatial footprints: 1.) physical distance (i.e., distance decay) , 2.)

type of trip/activity, 3.) the distribution of opportunities (i.e., available alternatives), and 4.) directional biases (i.e., social distance). The first factor, physical distance, is simply that people prefer to travel to locations that are spatially nearby, rather than farther away because it is less difficult than some place farther away. This pattern is known as a distance decay effect, and this idea stems in part from Tobler's first law of geography: near things are more related than far away things [220]. When making decisions about where people choose to travel, I expect residents will most often choose to travel closer to home rather than a location farther away because of the ease of travel and it is less expensive (i.e., less time, less gasoline). In the extreme if the classic urban village model were at work, we would expect for all activities to be concentrated within only the home neighborhood.

Perhaps the most obvious factor in determining where people choose to go is the particular type of activity itself. Put simply, different types of activities will likely have different spatial footprints. Different people will participate in different activities because they have different purposes for their trips, and these differences in purpose will sort people into different spaces. For example, the spatial footprint for a work location is conceptually distinct from a shopping location - where someone works is distinct from where someone shops. The participation in these different types of activities are expected to be determined by a number of factors, including where people are in the life cycle, family structure, their social networks, the sequence and combination of a trip with other trips, whether the trip is habitual or sporadic, and the duration of a particular trip [111]. Research from the LAFANS has shown that different activities are located at different distances away from the home [195], but research has yet to empirically demonstrate the selection process among different activity location choices. While there is not much theoretical guidance on different distance decays for various activities, I expect for amenity trips (e.g. to the grocery store) to have a steeper distance decay because residents are likely to travel to the nearest location since many grocery stores often have the same products, ease of travel (i.e., quicker, less gasoline), and the decision is more discretionary.

Participation in different types of activities likely sorts groups of people to different spaces of the city during different times of day (i.e., there is a temporal component with which people are in spaces). For example, due in part to differences in women and men in the workforce outside of the home, women participate less in urban areas during the daytime [121]. Race and income segregation patterns may constrain where people work [54], as well as when. Aging and point in the life course might also play a role. Young people are most often located in schools and colleges during the daytime, while elderly people are mostly restricted to their homes.

After deciding on a particular type of activity, the third factor suggests that the question than becomes on the distribution of opportunities for this activity in the area. People will likely evaluate where they choose to go based in part on the available alternatives [11, 146, 147]. For example, the grocery store that someone chooses to visit is explicitly a function of the range of available grocery stores in the area.[1] This idea follows from Hägerstrand (1970) who suggested that there are *constraints* for where people travel [76]. The characteristics of different opportunities might also shape the *feasibility* of gaining access into different locations (see also [110]). One extreme example is that the choice of where someone works is not simply just a choice of where they might potentially want to work, but the characteristics of those doing the hiring (i.e., on the receiving end).[2] I expect that the choice of an activity's location is determined by a variety of factors, including the characteristics of other similar locations, agglomeration, population density, the location of different land uses, social networks, mode of transportation, physical and social barriers, language, individual preferences, and street networks. A major contribution of this chapter is incorporating the characteristics of potential places that someone might travel when choosing where to go for a particular activity.

[1] A similar issue is noted when looking for a marriage partner [157]. In a sense, people select (and are limited too) partners from the local geographic area.

[2] An example from another context would be when someone is making a decision about buying a car. While individual preferences might play a role, the characteristics of the different potential cars are also likely quite salient. If I only looked at the car someone bought, this doesn't necessarily tell us much about how they chose this car among others.

The last factor suggests that directional biases shape spatial footprint patterns above and beyond physical distance, the type of activity, and the distribution of opportunities.[3] Directional biases allow for the possibility that people might choose to go to a location farther away, even though another location is closer [64]. They might also explain why someone might travel in one particular direction and not another. Directional biases are expected to be a result of a variety of factors, including where an individual has lived in the past, known travel patterns, information flow, social ties, personal preferences, and places with little social distance.[4] As a reminder from the last chapter, social distance refers to the idea of differences in various social categories (e.g., race, age, gender, income) between groups of people, and these differences are expected to have the consequence of less social interaction between groups [82, 171].[5] The more social distance between someone's home neighborhood and a set of potential destination neighborhoods, I expect them to travel to this area less often. Put another way, neighborhoods with more social similarity between residents might be expected to have more spatial footprint patterns between them.

Given citywide segregation patterns, it is expected that race and income similarity will situate many spatial footprint patterns, above and beyond the effects of physical distance. Research from Los Angeles Family and Neighborhoods Study (LAFANS) suggests that whites are more likely to interact with whites in their activity patterns to suggest a social isolation effect, while blacks and Latinos are expected to have more social integrated activity spaces [103].[6] Krivo and colleagues have examined this isolation in regards to how the disadvantage around people's homes compares with the disadvantage of the

[3] The idea of a directional bias stems from work in demography and geography looking at long-term migration patterns [64]. This literature focuses on how people are more likely to move to large population centers, rather than in any other direction. One distinction this chapter makes from prior work is by examining directional biases over the day, as well as directional biases in relation to social and physical distance.

[4] Additional individual preferences might also shape the directional biases of spatial footprints: prior locations, loyalty to particular businesses and other entities, fear and avoidance of some areas, attractiveness of other areas, and knowledge of other's experiences.

[5] Social distance is sometimes referred to as *blau space* [149, 141].

[6] Other research from the LAFANS suggests that when low-income groups have activities located in more wealthy areas, they are more healthy than low-income people who do not spend anytime in wealthy areas [95].

combination of various activity locations: work, grocery, school and church [115]. Their findings suggest a particular spatial pattern of social similarity/distance: the racial and economic disadvantage of individuals' residential neighborhoods is similar or exacerbated in relation to the neighborhoods of their routine activity locations (i.e., the average disadvantage over work, school, grocery, and church locations).[7] One challenge for these studies is that they only consider the destination location, and do not incorporate information on the potential for interaction between different groups.

Using data from the Los Angeles Family and Neighborhoods Study (LAFANS), this chapter helps fill this gap by examining a range of different activity locations: home, work, school, church, and grocery store. In a series of discrete choice models that include information on all Census tracts in the Southern California region, I examine how physical distance, land uses, street layout, individual preferences, and social distance impact where people choose to go for different activities from their homes. The results indicate that physical distance is the strongest determinate of location choice for all activities - more than all other measures combined. Each activity also has a distinct distance decay implying nonuniform accessibility. These findings indicate that many spatial footprint patterns are attracted and constrained by the geographic landscape of the area.

## 3.2 Data and Methods

This chapter of my dissertation examines the selection process of where people travel for different activities. Census tracts represent neighborhoods for this chapter, which is the most commonly used measure in the literature [187]. I use data from several sources, and the main source of data are from the first wave of the LAFANS data that was collected by the Rand Corporation from 2000 to 2002 (see [194] for more study information).[8] It is a sample of households in Los Angeles County California. The LAFANS is well suited for

[7] Residents in more advantaged residential neighborhoods were also shown to travel farther in their routine activity locations.

[8] Link to L.A.FANS Documentation: http://lasurvey.rand.org

this project because it captures the travel behaviors of respondents' daily activities, including work, church, grocery store, and school.[9] In 2000, Los Angeles county contained approximately 9 million people of which 45% are Latino, 31% White, 13% Asian, and 10% Black. The overall refusal rate for the sample was approximately 16% [196]. The data are a stratified random sample of households in Los Angeles County. The data are stratified by neighborhood poverty with an oversample of poor (60-89th percentile of poverty distribution) and very poor (top 10%) respondents. A total of 65 tracts were sampled: twenty tracts were allocated to both the poor and very poor stratum and 25 tracts were allocated to the non-poor (remaining 60% of poverty distribution). The data also oversample households with children under 18 by making them approximately 70% of the sample when they would have otherwise been 35%. Respondents were interviewed in person or on the phone and were allowed to take the survey in either English or Spanish. The sampling frame was solicited from 1990 census tracts. In wave 1, the project collected between 40-50 households from each of 65 Census tracts. There are a total of 2777 households with a home Census tract. All summary statistics for the data are presented in Table 3.1.

### 3.2.1 Dependent Variables - Destination Locations for Different Types of Activities

In the LAFANS data, adult respondents in the household reported their home location and several activity locations: work, grocery store, church, and children's school.[10] Each household's set of destination locations was geocoded and attached to a Census Tract by Rand. Less than 2% of children's school, church, and grocery store locations were located outside of Los Angeles County, while less than 7% of work locations were outside of Los Angeles County.

[9] I was also interested in examining the spatial distribution of day care locations. Day care locations were extremely rare in the data, and I did not proceed further with the analyses.

[10] The frequency of use for these different activity locations is unclear.

### 3.2.2 Independent Variables

#### Physical Distance

For each location, I computed a distance between the home and each of the four locations. Distances were computed as the ”crow flies” between tract centroids. I used Austin Nichols' vincenty program in Stata to compute these distances, which uses an ellipsoid model of the earth.[11] The distance in miles was logged (+1) in all of the models.

One complication for computing distances between the home and destination choice locations is instances when the destination choice location is within the same Census tract. In this instance, the distance between home and the "destination" in the same neighborhood is missing and undefined (since distance cannot be zero). Two approaches were used to account for this issue. The first approach takes the distance from the centroid to the nearest Census tract boundary.[12] As a second approach, I include an indicator for the Census tract within someone's own neighborhood. This approach effectively captures preferences for traveling within their own home neighborhood.

#### Intersection Density

A measure of the intersection density was computed to capture the street pattern of each neighborhood. This measure is commonly used in public health and urban planning literature to capture the connectivity of a neighborhood [27].[13] Neighborhoods with more connectivity are likely more accessible. An intersection is defined as a location where two or more street segments are coincident. Intersection section density is the number of intersections divided by the area of the Census tract.

[11] Another approach might use travel distance to account for the road network. The travel distance approach has been shown to produce approximately identical results to the”crow flies” method [17].

[12] Another approach might generate random points within each Census tract and take the average distance between points. This process might be computed for multiple iterations/imputations. The result from this average 'random points' approach is expected to be approximately identical to the nearest boundary approach, but future research will want to test this possibility.

[13] One study that tracked people's movement patterns for one weekday found that more street connectivity and more retail land use had a significant impact on the total distance that someone traveled over the day [59].

### Land Use

Land use data was obtained from the 2000 Southern California Association of Governments (SCAG). More details about the land use data are found in Appendix A. The data was initially in parcels, and it was apportioned to Census blocks by area and aggregated to Census tracts [16]. I created 6 categories of land use data: residential, industrial, retail, office, school, and other (e.g., parking, parks, agriculture, etc.). Each category represents the percent of some land use type in the Census tract.

### Grocery Stores

Mint global business data (also known as Orbis data) was obtained from Bureau Van Dijk. Although usually used for marketing and company report research, this database contains business information on over 100 million companies, including both public and private companies. I extracted the grocery stores using a 4-digit NAICS code. I then geocoded these locations, and created a count measure of the number of them in the Census tract.

### Churches

The locations of churches were obtained from the *Google* Places API. Google categorized whether a particular location was a church. A church includes any place of worship, synagogue, Hindu temple, mosque, or church. These data are a count of the number of churches in a Census tract.

### Neighborhood Demographic Characteristics

Information on the demographic characteristics of tracts is from the Census 2000. To capture places with school children, I use percent families with school age children (age 6-18). The racial composition of the neighborhood was assessed with 5 ethnic/racial groups: White, Black, Latino, Asian, and Other. The economic resources of the tract were captured with the median household income of the tract.[14] As a measure of residential stability, I include measures of the percent of vacant housing units and percent homeowners.

I also include measures of population density and employee density to capture the location of people at different times of day. Population density is from the 2000 Census, and it is the nighttime population density of residential areas. Employment density represents the daytime population of the Census Tract, and it is the number of employees who work in the neighborhood.[15] The number of employees was obtained from the Longitudinal Employee Household Dynamics (LEHD) data for 2001.[16] The data are from Bureau of Labor Statistics (BLS) Quarterly Census of Employment and Wages (QCEW), Unemployment Insurance files, and other federal administrative records.

#### Household Characteristics

Several household characteristics were measured with the LAFANS data, including household income, number of years living at a residence, whether or not someone was a homeowner, employed, owns a car, married, has children, respondent sex, respondent race and ethnicity, and age of respondent. Household income is per $10,000, and it is the sum of family earned income, asset income, and transfer income. Except for income, age, and years at residence, all of these characteristics are a series of indicator variables. The actual wording of questions is from the Census 2000.

### 3.2.3 Plan of Analysis

I use discrete choice models to capture a household's spatial footprint patterns. Discrete choice models are often used to capture when someone is making a decision among a set of alternatives.[17] One way to conceptualize these models is to imagine someone at home who

[14] Poverty and median income are correlated at .76.

[15] This measure may more precisely map onto the "busyness" of different neighborhoods. Future work will also want to incorporate information on non-employees to improve estimates.

[16] More information about LEHD Data can be found here: http://lehd.did.census.gov/

[17] For more discussion of these models, see Ben-Akiva and Lerman (1985) [11] and Bruch and Mare (2012) [28].

has decided to make a trip to the grocery store. They are now faced with a challenge of choosing a grocery store. The choice of which grocery store a person chooses to visit is crucially dependent upon the range of available grocery stores in their area. The selection of an activity location is the most preferable location given the other locations, and in this case the choice to make a trip is independent of the decision for where someone travels.

The selection decision of a household for a particular activity location (i.e. what grocery store they use) is a function of the characteristics of alternative locations. One challenge for discrete choice models is determining the set of alternatives - "alternatives" in this case represent Census tracts.[18] The set of alternatives - the choice set - are all Census tracts within the Los Angeles-Long Beach Combined Statistical Area. In other words, they are all potential target locations for where someone chooses to travel for a particular activity.[19] The Los Angeles-Long Beach CSA is comprised of Los Angeles County, Ventura County, San Bernardino County, Orange County, and Riverside County.[20] Rather than just characteristics of the home neighborhood, the data are structured as alternative specific in that for every household I include an observation of all potential target locations. I have 2777 households who reported a home Census tract and 3373 potential Census tracts in the Los Angeles CSA, this leads to a dataset of approximately 9.3 million observations (2777* 3373). Not every household reported every activity location: 1518 households reported at least one work location, 2433 a grocery store, 945 a church, and 1324 have children in school. The standard errors for the different alternatives are adjusted for the clustering within households. No issues were found for extreme outlier cases or multicollinearity.[21]

[18] Initially I tried to use smaller units of analysis (Census blocks), but the data was mostly missing at small units. As a result, I used tracts. Block groups were also substantially missing. The reason for the missing data at small units was the LAFANS restricted data version 2.5 is only released for some locations in blocks, while the version 2.0 is in tracts and more complete.

[19] I estimated models with two other possibilities for the choice set, and neither approach substantively altered the results. One approach restricted the choice set to just Census tracts in Los Angeles county. As another approach, I restricted the choice set to only tracts that included a potential activity location. Using the grocery store location as one example, I only included tracts in the choice set that had at least one grocery store in the models for selecting a grocery store location.

[20] No activities were located in San Diego or Imperial counties.

[21] One tract had excessively long commutes to all activity locations. The models estimated with and without this tract were substantively identical.

In what follows, I focus on four different models for each different activity - work, church, grocery store and children's school:

Model 1: *Same-Neighborhood Only* - This baseline model represents the classic urban village approach by suggesting that all spatial footprints are only within the home neighborhood.

Model 2: *Same-Neighborhood and Distance* - This model takes a step further by adding a measure of distance to various alternative locations.

Model 3: *Space and Land Use* - This model uses only 'space' measures to explain location choices without any characteristics of people. The *space* measures again include the same-neighborhood indicator and a measure of distance, but also now include street intersection density and various land use measures.

Model 4: *Neighborhood and Household Demographics* - The final model includes all information from the earlier models but now includes information on the target neighborhood, the extent of similarity between the target neighborhood and the home neighborhood, and household characteristics. These models effectively capture whether residents select similar neighborhoods based on where they start (extent of similarity) in relation to where they going (target neighborhood). In other words, these models capture "directional" biases and social distance preferences.

Table 3.1: Summary Statistics

| | Residence | | Work | | Grocery Store | | Church | | Child's School | | Southern CA | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| **Target Neighborhood** | | | | | | | | | | | | |
| Same-Neighborhood (0/1) | 1.00 | 0.00 | 0.13 | 0.34 | 0.15 | 0.36 | 0.09 | 0.29 | 0.21 | 0.41 | 0.00 | 0.02 |
| Distance (Miles) | 0.30 | 0.28 | 7.27 | 8.40 | 1.63 | 2.30 | 3.15 | 4.08 | 2.04 | 4.20 | 31.21 | 25.42 |
| Intersection Density | 0.65 | 0.33 | 0.57 | 0.34 | 0.68 | 0.38 | 0.64 | 0.33 | 0.61 | 0.32 | 0.49 | 0.31 |
| Population Density | 15088.81 | 11095.69 | 10049.52 | 9697.33 | 14700.71 | 12115.75 | 13622.10 | 9223.98 | 12956.51 | 9241.16 | 9849.68 | 9668.07 |
| % Residential LU | 48.22 | 28.94 | 36.34 | 27.97 | 48.33 | 28.21 | 46.75 | 27.84 | 46.88 | 27.32 | 50.16 | 27.44 |
| % Industrial LU | 6.13 | 12.60 | 17.83 | 24.57 | 6.83 | 13.00 | 6.11 | 12.70 | 6.33 | 12.79 | 6.05 | 12.47 |
| % Office LU | 1.31 | 4.23 | 3.59 | 7.13 | 1.04 | 2.61 | 1.11 | 3.04 | 0.77 | 2.00 | 1.11 | 3.20 |
| % School LU | 5.08 | 7.58 | 3.98 | 7.50 | 5.31 | 8.80 | 6.06 | 8.16 | 7.51 | 7.77 | 4.24 | 6.77 |
| % Retail LU | 4.46 | 6.70 | 5.77 | 7.49 | 7.57 | 7.36 | 5.75 | 6.38 | 5.19 | 6.15 | 5.08 | 6.48 |
| Employee Density | 1.08 | 1.97 | 4.51 | 10.09 | 1.43 | 1.61 | 1.43 | 2.57 | 1.22 | 2.11 | 1.11 | 2.96 |
| # Grocery Stores | 2.19 | 1.66 | 2.87 | 3.01 | 2.37 | 2.12 | 2.24 | 2.04 | 2.10 | 1.99 | 1.76 | 1.81 |
| # Churches | 3.80 | 3.20 | 4.25 | 3.74 | 3.89 | 3.36 | 5.21 | 4.16 | 4.24 | 3.35 | 3.42 | 3.59 |
| % Families with Children | 59.30 | 12.30 | 53.40 | 14.07 | 56.66 | 13.19 | 56.98 | 11.98 | 56.85 | 11.82 | 54.06 | 12.76 |
| % Black | 8.11 | 9.84 | 9.26 | 13.85 | 8.80 | 14.15 | 10.44 | 15.65 | 9.09 | 13.33 | 7.10 | 12.90 |
| % Latino | 55.01 | 29.25 | 45.26 | 30.16 | 49.80 | 29.50 | 50.08 | 29.96 | 50.15 | 29.18 | 39.00 | 28.14 |
| % Asian | 10.21 | 11.16 | 12.02 | 13.67 | 12.03 | 13.38 | 10.86 | 13.40 | 10.96 | 12.46 | 10.47 | 12.66 |
| % White | 23.98 | 25.18 | 30.25 | 27.22 | 26.56 | 25.50 | 25.87 | 26.81 | 27.06 | 26.61 | 40.34 | 28.94 |
| Median Income | 4.07 | 2.26 | 4.28 | 2.34 | 3.91 | 1.85 | 4.05 | 2.03 | 4.32 | 2.42 | 4.96 | 2.46 |
| % Homeowners | 43.59 | 26.99 | 42.61 | 27.20 | 41.89 | 25.05 | 42.71 | 24.31 | 47.78 | 25.71 | 55.50 | 26.03 |
| % Vacant Units | 4.84 | 3.61 | 5.10 | 5.09 | 4.55 | 4.20 | 4.57 | 3.49 | 4.49 | 4.35 | 5.28 | 7.22 |
| **Household Characteristics** | | | | | | | | | | | | |
| Household Income (per $10,000) | 3.99 | 4.59 | | | | | | | | | | |
| Residential Tenure (Years) | 7.27 | 8.87 | | | | | | | | | | |
| Homeowner (0/1) | 0.39 | 0.49 | | | | | | | | | | |
| Employed (0/1) | 0.64 | 0.48 | | | | | | | | | | |
| Own Car (0/1) | 0.75 | 0.43 | | | | | | | | | | |
| Married (0/1) | 0.56 | 0.50 | | | | | | | | | | |
| Kids (0/1) | 0.77 | 0.42 | | | | | | | | | | |
| Female (0/1) | 0.62 | 0.49 | | | | | | | | | | |
| Black (0/1) | 0.09 | 0.29 | | | | | | | | | | |
| Latino (0/1) | 0.57 | 0.50 | | | | | | | | | | |
| White (0/1) | 0.25 | 0.44 | | | | | | | | | | |
| Age (Years) | 41.22 | 13.67 | | | | | | | | | | |

*Note:* SD = Standard Deviation, LU = Land Use Area. Distance for residence is to the nearest boundary of the Census tract. Southern CA is the Los Angeles-Long Beach Combined Statistical Area.

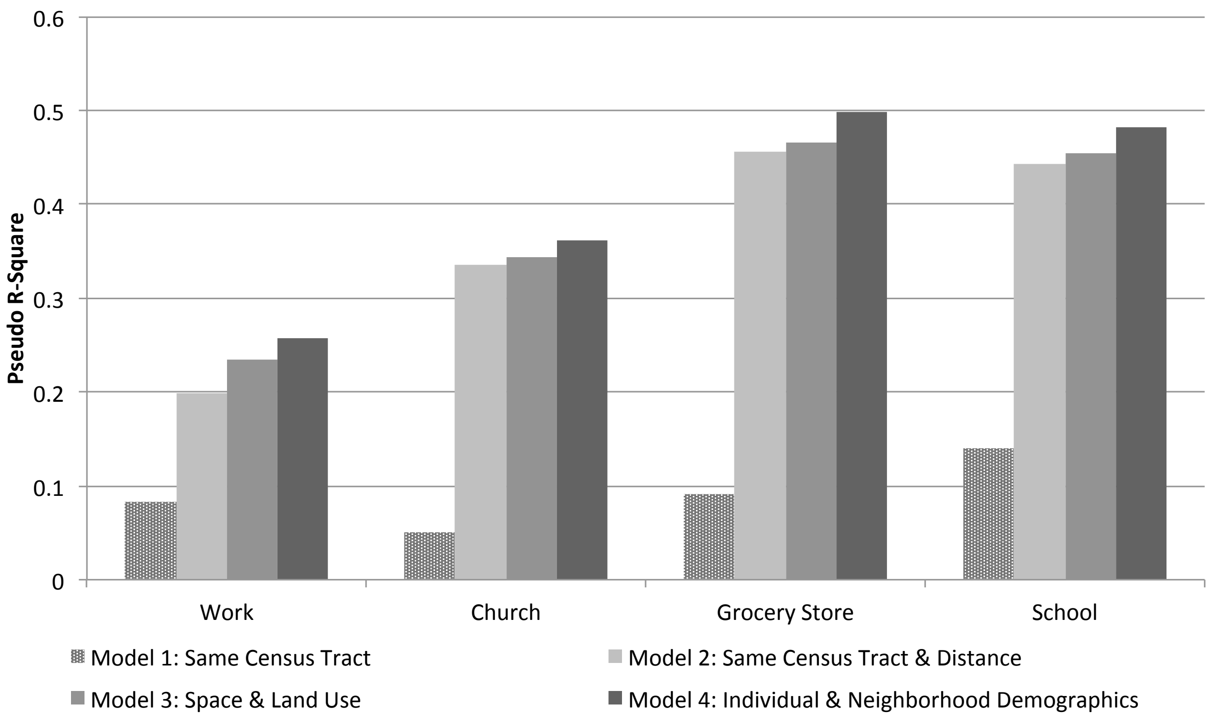
## 3.3 Results

### 3.3.1 Space, Distance, and Density

I begin by discussing the McFadden's Pseudo R-square from each of the four model specifications as shown in Tables 3.2 and 3.3. As can be seen in Figure 3.1, the addition of log distance in model 2 shows the greatest change in the amount of variance explained in location choice for all activities. With the addition of log distance, the R-square from model 1 to model 2 has a percentage point change of 11% for work, 29% for church, 36% for grocery store, and 30% for children's school. Although not shown in the tables, I also estimated models that only included distance without the same-neighborhood indicator. The Pseudo R-square for these models was .18 for work, .33 for church, .45 for grocery store, and .43 for child's school. A substantial part of the selection process for choosing all locations is distance, particularly for amenities. For all of the activities, model 3 with all of the physical spatial information shows the least model improvement of about an average percentage point change of 1% when compared to model 2. With the addition of various demographic characteristics of the potential neighborhoods and household characteristics in model 4, we see little overall improvement in the model fit with an average percentage point change of 2.5%. Taken as a whole, these results indicate that distance drives much of where people decide to travel for various activities, while other social and physical characteristics play a much more minor role in these selection processes.

When looking at each of the model 1's in Table 3.2 for all of the different locations, we see that this simple model suggests that residents are more likely to select an activity location when it is within their same-neighborhood. However, much of the variance is unexplained with this simple model. When looking at the summary statistics in Table 3.1 just 13% of work locations, 15% of store locations, 9% church locations, and 21% of children's schools are located within the same-neighborhood (i.e., same Census tract). While this model does implicitly have a measure of distance, when looking at model 2 that incorporates the distance to various activities and other potential neighborhoods, we see a clear distance decay for all activities.[22] As distance from the home increases, the probability of selecting a location for any of the set of activities is reduced. The same-neighborhood preference for churches is now no longer significant.

Figure 3.1: Pseudo R-Squares




[22] I initially tried to estimate models that did not log distance. These models had estimation issues. For the models that did run successfully, I used logged distance because the pseudo R-squares were higher for all locations, although the substantive results of the models were similar.

Table 3.2: Discrete Choice Models for Location of Work, Church, Store, and School: Same-Neighborhood and Distance Models

| | Work<br>Model 1 | Work<br>Model 2 | Church<br>Model 1 | Church<br>Model 2 | Grocery Store<br>Model 1 | Grocery Store<br>Model 2 | Child's School<br>Model 1 | Child's School<br>Model 2 |
|---|---|---|---|---|---|---|---|---|
| | Coef.<br>(SE) | Coef.<br>(SE) | Coef.<br>(SE) | Coef.<br>(SE) | Coef.<br>(SE) | Coef.<br>(SE) | Coef.<br>(SE) | Coef.<br>(SE) |
| **Target Neighborhood** | | | | | | | | |
| Same-Neighborhood (0/1) | 6.49732*** | 2.79568*** | 5.95045*** | 0.15904 | 6.58456*** | 0.14461* | 7.12705*** | 1.01222*** |
| | (0.08646) | (0.14546) | (0.11794) | (0.13155) | (0.06262) | (0.07159) | (0.07472) | (0.08995) |
| Log Distance (Miles) | | -0.98912*** | | -2.94970*** | | -3.81347*** | | -3.38269*** |
| | | (0.15952) | | (0.05237) | | (0.04253) | | (0.05396) |
| Log Distance * Log Distance | | -0.19582*** | | | | | | |
| | | (0.04006) | | | | | | |
| Intercept | -7.93532*** | -3.97814*** | -8.11980*** | -1.65283*** | -8.18662*** | -0.89342*** | -8.14666*** | -1.25042*** |
| | (0.01883) | (0.14819) | (0.01488) | (0.06846) | (0.01088) | (0.04313) | (0.01731) | (0.06272) |
| Pseudo R-square | 0.08296 | 0.19845 | 0.04984 | 0.33531 | 0.09087 | 0.45587 | 0.14003 | 0.44239 |

*Note:* SE = Standard error. $* = p < .05$; $** = p < .01$; $*** = p < .001$

Table 3.3: Discrete Choice Models for Location of Work, Church, Store, and School: Full Models

| | Work | Work | Church | Church | Grocery Store | Grocery Store | Child's School | Child's School |
|---|---|---|---|---|---|---|---|---|
| | Model 3 | Model 4 | Model 3 | Model 4 | Model 3 | Model 4 | Model 3 | Model 4 |
| | Coef. | Coef. | Coef. | Coef. | Coef. | Coef. | Coef. | Coef. |
| | (SE) | (SE) | (SE) | (SE) | (SE) | (SE) | (SE) | (SE) |
| Same-Neighborhood (0/1) | 2.96130*** | 2.35012*** | 0.17120 | -0.51005** | 0.15090* | -0.38005*** | 0.99616*** | 0.51087*** |
| | (0.15317) | (0.17400) | (0.13396) | (0.18903) | (0.07315) | (0.09910) | (0.09262) | (0.13702) |
| Log Distance (Miles) | -1.04565*** | -1.22455*** | -2.92298*** | -2.91286*** | -3.88598*** | -4.09370*** | -3.45967*** | -3.63623*** |
| | (0.16597) | (0.19210) | (0.05424) | (0.07955) | (0.04554) | (0.07252) | (0.05580) | (0.08240) |
| Log Distance * Log Distance | -0.17742*** | -0.16752*** | | | | | | |
| | (0.04103) | (0.04606) | | | | | | |
| **Target Neighborhood** | | | | | | | | |
| Intersection Density - Target | -0.52260*** | -0.25270* | -0.25483* | -0.15371 | -0.01050 | 0.32415*** | -0.63404*** | -0.24044* |
| | (0.10192) | (0.11637) | (0.10380) | (0.14733) | (0.06216) | (0.08020) | (0.09156) | (0.11847) |
| % Residential LU - Target | -0.00381*** | -0.00455** | 0.00197 | -0.00379 | 0.00823*** | 0.00077 | 0.00551*** | -0.00373** |
| | (0.00108) | (0.00149) | (0.00116) | (0.00195) | (0.00076) | (0.00117) | (0.00094) | (0.00144) |
| % Industrial LU - Target | 0.02683*** | 0.02155*** | -0.00211 | -0.01249** | 0.01086*** | 0.00757** | 0.00339 | -0.00442 |
| | (0.00139) | (0.00197) | (0.00257) | (0.00440) | (0.00152) | (0.00247) | (0.00205) | (0.00319) |
| % Office LU - Target | 0.06339*** | 0.03731*** | -0.02257** | 0.00022 | -0.04274*** | -0.01834* | -0.06275*** | -0.05181*** |
| | (0.00319) | (0.00483) | (0.00875) | (0.01495) | (0.00509) | (0.00919) | (0.00851) | (0.01487) |
| % School LU - Target | -0.00013 | -0.00350 | 0.01303*** | 0.01488** | 0.01178*** | 0.00177 | 0.02650*** | 0.03049*** |
| | (0.00445) | (0.00407) | (0.00279) | (0.00478) | (0.00251) | (0.00377) | (0.00171) | (0.00342) |
| % Retail LU - Target | 0.00525 | 0.01773*** | 0.00545 | 0.00884 | 0.04126*** | 0.05490*** | 0.00122 | 0.00338 |
| | (0.00405) | (0.00445) | (0.00473) | (0.00614) | (0.00207) | (0.00289) | (0.00418) | (0.00582) |
| # of Grocery Stores - Target | 0.05366*** | 0.03635** | 0.00460 | 0.01673 | 0.05685*** | 0.05653*** | -0.01029 | 0.00611 |
| | (0.00992) | (0.01141) | (0.01654) | (0.02099) | (0.01076) | (0.01251) | (0.01559) | (0.02011) |
| # of Churches - Target | 0.03694*** | 0.04245*** | 0.10147*** | 0.10512*** | -0.00029 | 0.00220 | 0.04429*** | 0.06947*** |
| | (0.00686) | (0.00814) | (0.00790) | (0.01023) | (0.00661) | (0.00978) | (0.00758) | (0.01124) |

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Table 3.3 – *Continued from previous page*

| | Work Model 3 | Work Model 4 | Church Model 3 | Church Model 4 | Grocery Store Model 3 | Grocery Store Model 4 | Child's School Model 3 | Child's School Model 4 |
|---|---|---|---|---|---|---|---|---|
| | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) |
| Population Density - Target | | -0.00004*** | | -0.00006*** | | -0.00003*** | | -0.00003*** |
| | | (0.00001) | | (0.00001) | | (<0.00001) | | (0.00001) |
| Employee Density - Target | | 0.07741*** | | -0.02651 | | -0.05796*** | | -0.00228 |
| | | (0.01406) | | (0.04273) | | (0.01707) | | (0.02180) |
| % Families with Children - Target | | -0.01436*** | | 0.01059 | | 0.00490 | | 0.02459*** |
| | | (0.00425) | | (0.00557) | | (0.00354) | | (0.00440) |
| % Black - Target | | -0.00375 | | -0.01902** | | -0.03385*** | | -0.02539*** |
| | | (0.00383) | | (0.00584) | | (0.00414) | | (0.00465) |
| % Latino - Target | | 0.00039 | | -0.00485 | | -0.02933*** | | -0.01831*** |
| | | (0.00255) | | (0.00351) | | (0.00251) | | (0.00307) |
| % Asian - Target | | -0.00420 | | -0.00688 | | -0.00913** | | -0.01170** |
| | | (0.00359) | | (0.00472) | | (0.00297) | | (0.00365) |
| % Other Race - Target | | 0.07041*** | | 0.05067 | | -0.07123*** | | -0.03225 |
| | | (0.01726) | | (0.02783) | | (0.01457) | | (0.02343) |
| Median Income - Target | | 0.03263 | | -0.01940 | | -0.29016*** | | -0.04731 |
| | | (0.03108) | | (0.05132) | | (0.04201) | | (0.05041) |
| % Homeowner - Target | | -0.00650** | | -0.00832* | | 0.01065*** | | 0.01244*** |
| | | (0.00231) | | (0.00395) | | (0.00236) | | (0.00331) |
| % Vacant - Target | | 0.01999* | | 0.00241 | | -0.00163 | | -0.01747 |
| | | (0.01015) | | (0.01651) | | (0.00943) | | (0.01195) |

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Table 3.3 – *Continued from previous page*

| | Work Model 3 | Work Model 4 | Church Model 3 | Church Model 4 | Grocery Store Model 3 | Grocery Store Model 4 | Child's School Model 3 | Child's School Model 4 |
|---|---|---|---|---|---|---|---|---|
| | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) |
| **Neighborhood Similarity to Home** | | | | | | | | |
| Population Density - Similarity | | 0.00001* | | -0.00001 | | 0.00003*** | | <0.00001 |
| | | (<0.00001) | | (0.00001) | | (<0.00001) | | (0.00001) |
| Employee Density - Similarity | | 0.04569** | | 0.05866* | | 0.01984* | | 0.00693 |
| | | (0.01404) | | (0.02949) | | (0.00910) | | (0.01319) |
| % Families with Children - Similarity | | 0.00315 | | 0.01555* | | 0.00538 | | 0.00134 |
| | | (0.00395) | | (0.00712) | | (0.00498) | | (0.00562) |
| % Black - Similarity | | 0.00806* | | -0.00140 | | 0.00656 | | 0.01277* |
| | | (0.00394) | | (0.00526) | | (0.00437) | | (0.00615) |
| % Latino - Similarity | | 0.00274 | | 0.00885** | | 0.00717** | | 0.00770* |
| | | (0.00186) | | (0.00328) | | (0.00253) | | (0.00306) |
| % Asian - Similarity | | 0.00283 | | -0.00012 | | 0.01392*** | | 0.00635 |
| | | (0.00337) | | (0.00521) | | (0.00418) | | (0.00509) |
| % Other Race - Similarity | | 0.06193*** | | 0.04452 | | 0.02479 | | 0.00975 |
| | | (0.01723) | | (0.02750) | | (0.02048) | | (0.02630) |
| Median Income - Similarity | | -0.02840 | | 0.00044 | | -0.01053 | | 0.01325 |
| | | (0.02509) | | (0.04290) | | (0.03288) | | (0.05017) |
| % Homeowner - Similarity | | -0.00563** | | -0.00685 | | -0.00579* | | -0.00603 |
| | | (0.00205) | | (0.00388) | | (0.00253) | | (0.00363) |
| % Vacant - Similarity | | 0.02147* | | 0.05696** | | -0.02172* | | 0.01964 |
| | | (0.01039) | | (0.01816) | | (0.00964) | | (0.01324) |

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Table 3.3 – *Continued from previous page*

| | Work Model 3 | Work Model 4 | Church Model 3 | Church Model 4 | Grocery Store Model 3 | Grocery Store Model 4 | Child's School Model 3 | Child's School Model 4 |
|---|---|---|---|---|---|---|---|---|
| | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) |
| **Household Characteristics** | | | | | | | | |
| Household Income (per 10k) | | -0.00991 | | 0.00560 | | -0.00788* | | -0.00369 |
| | | (0.00548) | | (0.00527) | | (0.00368) | | (0.00571) |
| Residential Tenure (Years) | | -0.00502 | | -0.00414 | | -0.00509** | | 0.00488 |
| | | (0.00292) | | (0.00263) | | (0.00170) | | (0.00364) |
| Employed (0/1) | | | | -0.03467 | | -0.05752 | | -0.00829 |
| | | | | (0.04864) | | (0.02935) | | (0.04188) |
| Homeowner (0/1) | | 0.15086** | | 0.12126* | | 0.18350*** | | 0.14262** |
| | | (0.04918) | | (0.04875) | | (0.03392) | | (0.04908) |
| Own Car (0/1) | | 0.06028 | | 0.04227 | | 0.06031* | | 0.01597 |
| | | (0.05422) | | (0.05916) | | (0.02934) | | (0.04587) |
| Married (0/1) | | 0.05100 | | -0.01959 | | 0.03663 | | 0.05240 |
| | | (0.04041) | | (0.04499) | | (0.02805) | | (0.03831) |
| Kids (0/1) | | 0.17301*** | | -0.00042 | | 0.02262 | | |
| | | (0.04633) | | (0.05867) | | (0.03176) | | |
| Female (0/1) | | -0.16842*** | | -0.05078 | | -0.03656 | | -0.00416 |
| | | (0.03757) | | (0.04201) | | (0.02625) | | (0.04039) |
| Black (0/1) | | 0.16625 | | -0.19953* | | 0.02881 | | 0.03389 |
| | | (0.09316) | | (0.08999) | | (0.05815) | | (0.08770) |
| Latino (0/1) | | 0.04819 | | -0.07767 | | 0.02733 | | 0.08317 |
| | | (0.06328) | | (0.07471) | | (0.04925) | | (0.07545) |
| White (0/1) | | 0.15088* | | 0.08235 | | 0.05889 | | 0.05822 |
| | | (0.07006) | | (0.07663) | | (0.05373) | | (0.08791) |

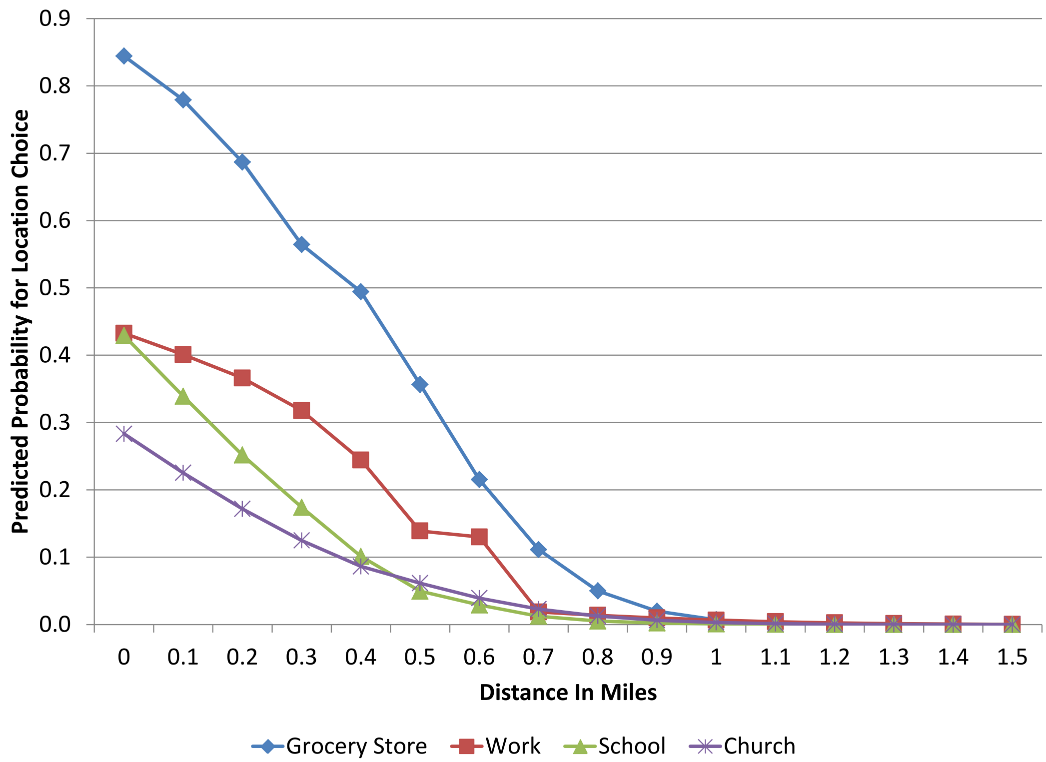
*Continued on next page*

Table 3.3 – *Continued from previous page*

| | Work Model 3 | Work Model 4 | Church Model 3 | Church Model 4 | Grocery Store Model 3 | Grocery Store Model 4 | Child's School Model 3 | Child's School Model 4 |
|---|---|---|---|---|---|---|---|---|
| | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) |
| Age (Years) | | -0.00275 | | 0.00141 | | 0.00110 | | 0.00309 |
| | | (0.00207) | | (0.00187) | | (0.00109) | | (0.00185) |
| Intercept | -4.22187*** | -2.62113*** | -2.13589*** | -0.41842 | -1.68083*** | 2.07155*** | -1.30941*** | -0.79527 |
| | (0.17546) | (0.37695) | (0.13555) | (0.52120) | (0.08905) | (0.32686) | (0.12557) | (0.46037) |
| Pseudo R-Square | 0.23427 | 0.25734 | 0.34383 | 0.36079 | 0.46524 | 0.49818 | 0.455 | 0.48268 |

*Note:* SE = Standard error, LU = Land Use. $* = p < .05$; $** = p < .01$; $*** = p < .001$

Figure 3.2: Distance Decay Predictions for Activity Location Choice




When looking at Table 3.3, we again see a similar pattern for *same-neighborhood* and distance. Figure 3.2 has the predicted probabilities for each activity choice from model 4 in Table 3.3.[23] All locations show a clear distance decay from the home. Locations in the same neighborhood for all activities show steeper distance decays. The distance decay of grocery store is the steepest, while churches, schools, and work are flatter. The change in the predicted probability of selecting a location between the home and a half-mile is 48%

[23]To plot this figure, all of the variables are set at zero, except for distance, same-neighborhood, and the intercept. Each plot covers approximately 95% of the range of distance values in the data. These plots are a weighted average between an activity's distance decay that are inside the home neighborhood and the same activity's distance decay outside of the neighborhood (weighted by proportion of data within a particular distance threshold).

for grocery store choice, 29% for work, 37% for school, and 22% for church.[24] The *same-neighborhood* effect for churches and stores actually flips signs in the fourth model to suggest that residents are traveling to nearby neighborhoods, but not exactly in the same Census tract. This result suggests that most activity locations are not captured in the urban village approach.

Models 3 and 4 in Table 3.3 include the opportunity for various selection location decisions. For example, when selecting a grocery store, I include a measure of the number of grocery stores in the target tracts. Choice of grocery store and work were more likely in neighborhoods with more grocery stores. More churches in the neighborhood were associated with more work, church, and school location choices.[25]

When examining the street connectivity in model 4, store choice is more likely when there are more intersections, while work and school choices are less likely in tracts with more intersections. Looking at the land use measures, we see that more residential land use indicates respondents are less likely to choose this tract for work and school. Neighborhoods with more industrial and office land uses are more likely chosen for work locations. On the other hand, more industrial and office land uses are less likely in neighborhoods with reported church, grocery store, and school selections. Neighborhoods with more school land uses are more likely chosen for church and school activity locations. Work and grocery store choice is more likely in neighborhoods with more retail land use. Take as a whole, the land use results display patterns that might be expected given each particular type of activity, including more work locations in industrial and office areas, more retail at store locations, and more schools in school and church areas.

[24] Although not shown, I also plotted each activity's distance decay for whether it was within and outside of the neighborhood. There is a clear shift when inside vs. outside of the neighborhood when looking at the distance decay plots for work choice, while the other activity types are much smoother.

[25] It is unclear when a respondent is actually using a particular activity location. As one way to assess this issue, I also estimated models that included a series of dummies for the day of week and month that a household responded to the LAFANS survey. Almost all of these indicators were not significant and their inclusion did not alter the results.

### 3.3.2 Target Neighborhood Demographics and Neighborhood Demographic Similarity

I now turn to discussing the results of the neighborhood demographic characteristics. When looking at the fourth models in Table 3.3, one set of covariates is labeled as "Target Neighborhood" and another set is "Neighborhood Similarity." The "Target Neighborhood" represents the characteristics of all of the potential neighborhood destinations. "Neighborhood Similarity" is the absolute difference of the target neighborhood and home neighborhood. To make this change score into a measure of similarity, this difference score is than multiplied by negative one. Higher values indicate more neighborhood similarity between home and target neighborhoods. In other words, these models assess not only the available "target" neighborhoods, but also how "similar" they are to their home neighborhood.[26] Generally, neighborhoods with more similarity are expected to have less social distance and therefore be more likely to be chosen/selected.[27]

Starting with the "target Neighborhood" characteristics in Table 3.3, neighborhoods with more population density are less likely chosen for work, church, grocery store, and children's school activity locations. Work locations are selected in neighborhoods with greater employee density, which is expected given that employee density is capturing the opportunity for work locations. One oddity in the findings is that grocery store locations are less likely to be chosen when in neighborhoods with more employees.[28]

[26] I also tested a series of interactions between the target and similarity measures. These models are shown in *Appendix B*. While there were significant effects, the substantive size of the effects were quite small and therefore I do not discuss them further.

[27] I also estimated models that only included the target neighborhood and similarity neighborhood demographic measures. The Pseudo R-Square for these models was .09 for work, .13 for church, and .18 for school. The store choice models had estimation issues. I also attempted to estimate models with only the neighborhood similarity measures, and these models had estimation issues for the store and school choices. For work choice, similarity measures accounted for .04 percentage points, while .09 percentage points for church locations. Finally, I also estimated models with just the target neighborhood characteristics, and the Pseudo R-squares for these models were .04 for work, .02 for church, .02 for grocery store, and .01 for school choices. These results suggest that other than physical distance, the next most important set of predictors are the social similarity measures (i.e., social distance), at least for work and church locations.

[28] I also estimated models with nonlinear terms for population and employee density. While these effects were significant, they are exceptionally tiny, and thus I do not include them here.

Children's school location choices are more likely in neighborhoods with more families with children. Holding all other variables at zero and constant, a one standard deviation increase in families with children in the target tract is associated with a .04 increase in the predicted probability of selecting a child's school location, and this effect is quite small.[29] Work selection choices are less common in neighborhoods with more families with children. A church, store, or school location are less likely chosen in minority neighborhoods than white neighborhoods. Neighborhoods with a larger other race/ethnicity compared to whites are more likely to be selected for work. Neighborhoods with more median income were less likely to be chosen for store locations.[30] A store or a school in a neighborhood with more homeowners was more likely to be chosen, while a work or church with more homeowners was less likely to be selected. Neighborhoods with more vacant units are more likely to be selected for work.

Now turning to the *similarity* results, when respondents chose a work or store location, they were more likely to choose a location that had similar population and employee densities. Choice of church location was also more likely in neighborhoods with more similarity in employee density and % of families with children. Neighborhoods with similar amounts of vacancies were more likely to be selected for work and church locations, but less likely for store locations. While only significant for choice of work and grocery store, more similarity of homeownership was less likely selected for all activities. Activity locations are often not in neighborhoods with similar levels of homeownership.

When looking at the findings for the social similarity results in regards to race/ethnicity, we see that activity location choices are more often between neighborhoods that are racially similar. Neighborhoods with more similarity in percent black are more likely selected for work and school locations. Neighborhoods with greater similarity of percent

[29]This effect was captured with one standard deviation increase from the mean with this formula: (P(school = 1) = (exp(coef * (mean + 1 std. deviation))/(1 + exp(coef* (mean + 1 std. deviation))) - (exp(coef* mean)/(1 + exp(coef* mean))). It represents the change in the probability after a one standard deviation increase from the mean.

[30]I tested nonlinear median income effects, and none were significant.

Latino are more likely selected for church, grocery store, and children's schools. Neighborhoods with more similarity in percent Asian are more likely for grocery store choices. Whereas the *target* neighborhood effects suggested that minority neighborhoods were less likely to be selected for all activity locations, we see that neighborhoods are also more likely to be chosen when there is racial *similarity* among residents. This finding suggests that racial homophily and accordingly neighborhoods that are more similar in regards to social distance are more likely to be selected for various locations even after controlling for physical distance and a variety of other factors.[31]

### 3.3.3 Household Characteristics

Finally, I briefly mention the results of the household characteristics.[32] When examining the characteristics of households in Table 3.3, these effects indicate the likelihood of respondent's going to different activity locations, and these control variables account for individual preferences.[33] Households with more income less frequently went to the store, while households that own a car more often visited the store.[34] Households who have lived in the neighborhood longer reported few trips to the store. For all locations, homeowners more frequently went to work, church, the grocery store, and children's schools. Households with children and males had a greater likelihood of reporting work locations. White

[31] I also estimated a series of models with interactions between distance and the neighborhood similarity measures. These models capture how the extent of similarity varies with distance for choice of activity location. No interactions were significant for school or church locations. The interaction between similarity of population density and distance was significant for work and store choice, but the differences were quite small. At distances less than a half mile, residents choose areas with less similarity of population density, but at distance of at least a mile, there were no longer substantial differences. A similar finding was shown for similarity of employee density and distance for store choice. Residents with more similarity of income between home and store were more likely to choose stores closer to home. Residents with low similarity between home and store were shown to be more likely to travel to the store up to approximately a half-mile, but no differences were observed after a mile.

[32] Although not shown in the tables, I also estimated models that only included these household characteristics and no other predictors. All of the Pseudo R-Squares for these models was $< 1\%$, which indicates that individual preferences explain substantively very little of the selection of various activity locations.

[33] The employed indicator was removed from the work location model because all respondents had to be employed for this question. Similarly, school locations were only asked for respondents with children. The kids indicator was removed for school location models.

[34] I also tested models with an income squared term, and it was not significant in any of the models.

respondents reported a greater likelihood for work, while black households reported fewer church locations.[35]

## 3.4 Discussion

This chapter of my dissertation focused on neighborhood accessibility by examining how households select different activity locations, including work, grocery store, church, and children's schools. The results indicate that spatial footprint patterns are structured by physical distance and social distance. The spatial footprint patterns are mostly determined by physical distance, rather than social demographic characteristics. It was particularly striking the robust impact of physical distance on spatial footprint patterns - on average a third of the selection effect for the different activity choices was explained with physical distance.

Although physical distance was the star of the show, the land use characteristics were connected to different activity patterns. School land use for children's school choice is the most obvious in this regard. Office and industrial land uses were found with work choices, and grocery store choice moved with retail areas and grocery stores. These findings suggest that land uses are implicitly the basis of different spatial footprint activity spaces.

The results suggest distinctions between the different types of activities, particularly for work locations. On the one hand, distance was the most important predictor in determining selection for all activity choices. On the other hand, each of the different

[35] I also tested models with interactions between the household characteristics and distance. These models are shown in *Appendix C*. These models test whether different households characteristics have different distance decay functions. The substantive sizes of these interactions were quite small, and thus I do not report them in tables, but briefly summarize the findings here. Households who have a car work farther from the home than households without a car. People who do not own a home work closer to home than people who are homeowners (i.e., renters work closer to home). Black households reported being less likely to go to church nearby their homes than non-Black households. When looking at the store locations, respondents who are not homeowners are more likely to go to the store nearby their homes than homeowners. Households with cars travel farther to the store than households without cars. Married households go to the store farther from their home than non-Married households. Latino households selected store locations closer to home than non-Latino households. Unemployed residents travel closer to home for school than employed residents. Households with younger people live closer to schools than those that have older people.

activities had a unique footprint. As such, it may not be appropriate to combine different types of trips into one total measure for all different activities. While some research has made a distinction between *obligatory* trips (i.e., work and school ) and *discretionary* amenity trips (i.e. grocery store) [111], this categorization does not quite work for this study since each trip had a distinct spatial footprint. For example, church locations exhibited a fairly flat distance decay and this might indicate that choice of church is less impacted by distance (i.e., choice of church is likely less dependent on space), nonetheless, a clear distance decay was observed. School choices are also a bit unique when compared to the other trips because they are likely bounded by school catchment areas.

Work locations demonstrated a more distant, distinct, and complicated footprint pattern when compared to the other activity choices. Unlike the other locations observed, the distance decay of work locations had more abrupt changes and a longer tail. The effects of families with children and employee density of the target choices also provide evidence of a distinction for work trips compared to other activity locations. The spatial distribution of where families are located across the city is particularly important for shaping the work locations of residents. With many respondents not working and living in the same locations, we might expect for people to be attracted to neighborhoods that have fewer families living there. A similar effect is shown when looking at the negative effect for the similarity of homeownership - work choices are much less likely in neighborhoods with similar amounts of homeownership between work and home neighborhoods. Finally, during the time period of data collection (2000-2002), downtown Los Angeles had exceptional changes in population density during daytime work hours and nighttime hours, and there were few people actually living downtown. Taken as a whole, the findings suggest that even after adjusting for physical distance population flows at different times of day are more salient for work choice, while discretionary amenity activities (i.e. grocery store choice) appear to be more of a function of social distance.

Different types of activities were also impacted by the racial/ethnic composition of the target locations, as well as the social similarity between different neighborhoods.[36] Church, grocery store, and children's school choices were always less likely in target neighborhoods with larger racial/ethnic minority residents compared to white residents, even after controlling for a variety of characteristics. The lack of these amenities suggests a form of spatial isolation. On the other hand, the similarity findings for racial/ethnic composition suggest that different activity choice patterns are most often in areas shown to have less social distance. In other words, the home neighborhood and activity choice neighborhood were often similar in regards to racial/ethnic composition, and this finding is suggestive of a homophily preference for spatial footprints.

The notion of an ethnic or immigrant enclave suggests that spatial footprint patterns will be preferred for areas with more social similarity (less social distance and more homophily) in regards to race and ethnicity. These patterns might be considered a function of ethnic enclaves within different cities (e.g. Chinatown in downtown Los Angeles). For example, similarity of Latino residents between the home and activity location were often predictive of church, grocery store, and school choice. Given that the spatial distribution of the ethnic enclave is often difficult to measure, future research might extend these findings by using the spatial footprint of residents to explicitly measure the spatial distribution of ethnic or immigrant enclaves. Nonetheless, these enclaves also suggest potentially detrimental patterns by socially and spatially isolating residents from the rest of the city [232].

The results indicate that spatial footprint patterns and people's daily lives are not neatly packaged into one neighborhood, which casts further doubt on the urban village model of only using one Census tract to represent neighborhood processes. Even in relatively large neighborhood units such as Census tracts, the results suggest that the urban village might only be capturing the nighttime residential locations of when people are simply in their home neighborhoods, and do not adequately address where people travel

[36] While only focused on one type of social distance characteristic, criminological research has found that social similarity in regards to resource deprivation is salient for homicide patterns [151]. The findings from this study indicate that journey to crime patterns might be situated within socially similar areas.

for different trips. The selection of grocery stores and children's schools often had short and steep distance decays within the home tract or nearby tract, while the distance decays of churches and work choices were much flatter. These patterns suggest that one census tract will not bracket individuals' entire social lives; yet on the other hand, individuals' spatial footprint patterns are not random and traveling all over the city.

Overall, the distance decay patterns were fairly smooth. These distance decays have consequences for how neighborhood researchers might measure nearby neighborhood processes. Most often the nearby area is captured with a contiguity measure (i.e. tracts that are nearby/touch a focal nearby with a "queen" or "rook" conceptualization) or a distance based measure. If a contiguity approach were at work, the distance decays would not have shown such a smooth decay pattern inside and outside of the home neighborhood. Although future research might explicitly test different conceptualizations of the "W matrix", these patterns suggest that distance based measures with a distance decay as a conceptually and empirically superior measure of the nearby area.

With people traveling to different spaces at different times, we might conceptualize different neighborhood boundaries as having elasticity. Different spatial footprint patterns would be one way to gauge the extent of a neighborhood boundary and area of influence. The distance decay of individual's spatial footprint patterns can be used to estimate the distance decay of the entire neighborhood. This approach would effectively incorporate the spatial footprint into conceptualizations of the nearby area (i.e., "the W matrix"). Future research might use this study of individual movement patterns to understand how the nearby area matters for the focal neighborhood. One approach might use the different coefficients from the models to estimate explicit distance decays for each demographic variable.[37] As shown in *Appendix C*, a series of models were estimated that included interactions between household characteristics and distance. The coefficients from these interactions could be used to scale the decay of the nearby area, as well as estimate the size

[37] Two characteristics are salient for understanding distance decay functions: 1.) the size and shape of the area (this is the "distance" component) and 2.) the shape/drop off of the area (this is the "decay" component).

and shape of the nearby area. The coefficient estimates can be incorporated into models by weighting them in the W matrix. These estimates might further be improved with interactions with the land use variables.[38] As a result, each neighborhood covariate will have a distinct distance decay. Moreover, a weighting scheme might be developed to average across different spatial footprint activities. This approach might be compared with other empirical specifications of the W matrix, including rook, queen, and inverse distance. Or, these might be incorporated into agent-based simulations. Nonetheless, the dominance of distance in the models suggests that distance alone might be adequate for specifying the "W matrix" for most purposes, and thus whereas variable specific specifications would improve the model, this will likely not result in much substantive importance.

This study has some limitations. First, this project does not explicitly capture when and for how long people are located in these different locations.[39] The incorporation of population density and employee density into the models in this chapter is a first step in examining this issue. Employee density arguably captures a part of daytime activity, and population density is a measure of the nighttime activity. Whereas population density had some significant but quite small effects, employee density was consistently associated with work, church, and store choices. Future work might examine this duration issue further by capturing when people are actually using these different spaces with location-based systems (i.e. cell phones) or time use surveys.[40] Second, I also do not know whether people would

[38] I initially estimated these models, but I decided not to include them because they did not have much theoretical insight for the different model specifications. Even still, the substantive effects were quite small.

[39] Kwan has shown that most discretionary travel occurs at night [122]. Similarly, above and beyond distance, individual travel behavior is impacted by facility hours (i.e., when is the restaurant open?) and public transit times (e.g., the subway train schedule situates people at regular intervals)[223] (see also [6]). GPS data has also shown that youth travel patterns are fairly stable (i.e., not random) over the week, and youth often travel farther on the weekends and at night [227, 228]. There has been little work on other time scales such as activity patterns over different seasons (children in summer when no school), holidays, or much of discretionary travel.

[40] Prior work has also suggested that different activities occur "more or less in cycles that are regularly timed. Identifying these cycles is the first phase in being able to predict and plan for activities in cities" [64, p. 290]. Regularly scheduled meetings, church times, school, shopping, and work are consistently temporally clustered around the same hours of the day and week [64, 77, 200]. The next step for this line of research to understand how different activities are sequenced together over time. This is an issue that I revisit in chapter 5 when examining crime.

always start from their homes when choosing a particular location. While the home is a natural starting point, I am unable to determine where people might travel within the context of other trips or the ordering of different trips.

My results are a reminder for social science researchers to explicitly incorporate space into their conceptualization. Rather than explicitly discussing processes of only major social attributes, I find that physical characteristics explain many people's spatial footprint patterns. This is not to say that social attributes are not important, but recognizing that they exist in a particular spatial temporal context. While researchers often call for longitudinal research in their area of interest, the next step for this line of research is to incorporate space. This implies understanding not just whether people have some particular social attribute, but an examination of how these attributes of people exist, interact, and have consequences within a space. While a focus on space is reasonably conceptually, there are also considerable empirical gains in regard to measurement and model parsimony. The last model in Table 3.3 contains approximately 30 additional "social", individual and neighborhood demographic variables. While the pseudo R-square did increase with the incorporation of these 30+ social variables, the model with distance and land use characteristics explained on average over 93% of the variance in model 4 (model 3 pseudo R-Square / model 4 pseudo R-square). Measurements of the physical world also likely have less measurement error (i.e., the number of intersections in a city) than measures of social processes (i.e. collective efficacy, social ties). While no social process is completely spatially determined, this of course does not mean that space should be ignored all together as done in most social science research outside of geography.

This chapter has examined the accessibility of different neighborhoods for different activities. In what follows in the next chapter, I examine how these spatial footprint patterns impact the neighborhood cohesion, informal social control, and collective efficacy. The next step is whether these spatial footprint patterns make a difference for different neighborhood processes. For instance, is there any evidence that the range of spatial footprint patterns have an impact on a neighborhood's ability to provide informal social control? One pattern might suggest a community of limited liability, and more distant spatial footprints would be associated with less collective efficacy in the home neighborhood.

# Chapter 4

# What are the consequences of spatial footprints for perceptions of neighborhood processes?

## 4.1 Introduction

This chapter of my dissertation examines the impact of spatial footprint patterns for residents' perceptions of collective efficacy in their neighborhood. While collective efficacy theory has dominated much of neighborhood research since the late 1990's (e.g., see [51, 142, 188, 189, 190, 192, 193, 191]), we have remarkably little work on what brings about collective efficacy. In other words, where does it come from? Sampson et al. (1997) highlight this issue by examining individual and neighborhood demographic characteristics in their original paper, but there is a dearth of work exploring other factors associated with collective efficacy. In what follows, I suggest land uses and spatial footprints can advance this research.

Collective efficacy is rooted in social disorganization theory. Shaw and McKay's seminal work on social disorganization theory suggests that residential instability and ethnic heterogeneity reduces trust among neighbors [203]. The instability, poverty, and ethnic heterogeneity of the neighborhood are posited to make social ties among residents less likely. This idea implies that the lack of ties between neighbors might result in more crime because of less informal social control. Building on this work in Chicago, Sampson and colleagues undertook an enormous data collection effort and from this work they introduced the concept of collective efficacy: residents' perception for mutual support (i.e., cohesion) and their willingness to intervene (i.e., informal social control). Collective efficacy theory focuses on perceptions of how other people in the neighborhood might behave when confronted with a neighborhood problem (for a review of studies using collective efficacy see Appendix C in [101]). Collective efficacy theory suggests that neighborhoods with residents who perceive their neighbors as having more shared expectations and willingness to become involved in a neighborhood problem as being able to better control crime.[1]

Collective efficacy focuses on the "shared expectations" among residents. This is often referred to as the *cohesion* dimension of collective efficacy. The idea of a shared expectation implies some degree of mutual agreement, but one challenge is that it is unclear how residents' come to this agreement. It might be the case that some solutions to collective action problems leave groups of residents powerless even in the most collectively efficacious communities.[2] In other words, how representative is the collective efficacy of the neighborhood? What is the spatial distribution of a neighborhood's collective efficacy? These questions suggest a need to understand the process of collective efficacy, and how a particular solution to a collective action problem becomes mutually agreed upon and eventually shared among residents.

One question this raises is: how do residents' form perceptions about their neighborhood? In this chapter, I consider the effect of spatial footprints for forming perceptions about the neighborhood. Spatial footprints are expected to matter because of their impact on an individual's awareness of different issues as he or she travels around to different activities, as well as through community engagement and social ties. Before turning to the spatial footprint and its impact on perceptions of neighborhood processes, I briefly review the two main factors in the literature: social ties and community engagement.

The most common approach in the literature suggests that shared expectations and trust are developed through social ties [226]. Drawing from social disorganization theory and systemic theories, residential instability and ethnic heterogeneity are expected to diminish the number of social ties in the neighborhood. Through social ties (e.g., friendships and

[1]Collective efficacy has also been linked with residents' having better health [41].

[2]A collective action problem might also have multiple viable solutions.

kin), residents may be more likely to perceive more social support from their neighbors and be more likely to come together to address a collective action problem. Sampson (2012) highlights several challenges for work on social ties and their relation to neighborhood crime: many ties exist in poor neighborhoods where there is often more crime, and more ties can be associated with more delinquency (i.e. gangs)[191]. Although not examined in prior research, it is also less clear from this research whether ties are already formed and existing, or whether residents form new ties as a result of a collective action problem.[3]

To address the challenges noted by Sampson (2012), collective efficacy researchers implicitly suggest a second approach for developing collective efficacy: civic engagement. Participation in community organizations may help residents perceive more shared responsibility of their neighborhood [173]. Similar to the last approach focusing on social ties, civic engagement is again expected to be rooted in residential instability and the ethnic heterogeneity of the neighborhood, but in this approach, residents are expected to participate in different civic institutions (e.g., community organization) depending on whether the perceive the institution as legitimate [191].[4] Research in this area has yet to examine the process of how residents obtain knowledge about different civic institutions, or how residents coordinate together to solve a neighborhood problem.

### 4.1.1 Spatial Footprint and Perceptions of Collective Efficacy

The spatial footprint of residents may be crucial for understanding perceptions of neighborhood processes and collective action problems. As residents travel to various activities within and outside of their neighborhood, they might form perceptions for how they expect their neighbors to act when confronted with a neighborhood problem. Residents may gain knowledge, information, awareness, and gossip about neighborhood

[3]On a daily time scale, most ties might be expected to be already formed and existing.

[4]Another commonality to both approaches is that they suggest a process of trust developing over a long period of time [101].

issues as they participate in various activities in the neighborhood (e.g., going to the grocery store) that are not based directly on their social ties or civic engagement. Residents might also become aware of an issue while on their journey to an activity. Research to date has yet to test this these possibilities.

Even still, participation in community organizations and social ties may well have an impact on collective efficacy, but both of these approaches often imply some degree of a spatially and temporally coordinated solution of people meeting to address a neighborhood problem. Patterns of spatial footprints are likely essential in this coordination. Spatial footprints situate face-to-face interaction between residents, which may improve or diminish the neighborhood's ability for collective efficacy. Drawing from the previous chapter, distance between residents, community organizations, and their activity patterns may situate whether residents actively engage in the neighborhood.

The land uses of the city might also play a role in residents' perceptions of collective efficacy. As was shown in the previous chapter of this dissertation, different land use patterns implicitly situate different spatial footprints. One study from the Los Angeles family and neighborhood study found that residents with a park and less disadvantage in their neighborhood perceived significantly more collective efficacy [41]. Qualitative research from St. Jean (2007) suggests that retail areas including restaurants and grocery stores may inhibit the potential for collective action [101]. Office, industrial, and school land uses in the neighborhood might explain residents' perceptions of collective efficacy, but no work has tested these possibilities. For example, residents with a school in their neighborhood may have more awareness and involvement in community issues. Many community members' spatial footprints intersect at their children's schools because of their children, but also because many meetings for community organizations take place at schools. When residents live closer to school, they also may be more likely to participate in these meetings.

### 4.1.2 Consequences of Spatial Footprints for Collective Efficacy

The spatial footprint may have at least three different consequences for a resident's perception of collective efficacy. One consequence suggests that spatial footprint patterns may not have any impact on collective efficacy, cohesion, or informal social control. Advances in technology paired with the fact that people have the ability to communicate without physical interaction implies the possibility that distance and footprint patterns may not have an impact on collective efficacy. In this view as suggested by Thomas Friedman, the "world is flat" [63].

Another consequence would suggest that spatial footprints do matter, but it is not necessarily clear whether spatial footprint patterns would improve residents' perceptions of their home neighborhood or be more critical (or even some combination of both). More distant spatial footprints might *improve* the shared expectations and collective efficacy of the neighborhood. Drawing from Hunter [93, 94], residents traveling outside of the neighborhood might imply social ties, information, and other resources that are not readily spatially available in the home neighborhood. Sampson's (2012) work on access to political elites and community organizations in the city also suggests a more distant spatial footprint as being beneficial to the neighborhood.

Another consequence suggests that more distant spatial footprints may *diminish* the collective efficacy of the home neighborhood. Drawing from the community of limited liability literature [70, 71, 100], one study focusing on the spatial distribution of social ties suggests that more distant social ties are associated with household's perceiving less cohesion [17]. This implies that residents with more distant spatial footprints might perceive less collective efficacy in the home neighborhood because they are spending less time in the neighborhood. More time outside of the neighborhood might suggest less awareness of different problems. Another unexplored possibility is that different activities might also be a factor. Residents who travel farther for work might be less likely to participate in local neighborhood organizations due to the challenges of commuting, but no research has tested this possibility.

The purpose of this chapter is to examine how spatial footprints have an impact on residents' perceptions of collective efficacy. Whereas most research combines individual perceptions of an area to form a global neighborhood measure, my focus is on a respondent's household collective efficacy. This is different from conceptualizing the shared expectations for a neighborhood because the focus is on how a person perceives himself or herself a part (or not part) of the efficacy of the collectivity, rather than global measures of the collective efficacy of the neighborhood. While both approaches are reasonable depending on the question of interest, I focus on residents' perception for two reasons: First, qualitative research suggests that collective efficacy is not a stable global construct, but in fact more fluid, varied, and micro across space [101]. In addition, given the fluidity of different footprint patterns, global measures might not adequately capture the proper spatial reference area of collective efficacy. Second, residents' perceptions are implicitly the foundation of generalized neighborhood collective efficacy measures. As noted earlier, it is also not clear how residents form a mutually agreed upon solution to a collective action problem, and this suggests a need to understand individual perceptions of collective efficacy.

## 4.2 Data and Methods

To test the consequences of spatial footprints for households' perceptions of collective efficacy, I use the Los Angeles Family and Neighborhood Study (LAFANS). This is the same data as discussed in the previous chapter. Neighborhoods for this project are represented by Census tracts, which is the most commonly used measure in the literature [187].

As discussed in the last chapter, I use data from several sources, and the main source of data are from the first wave of the LAFANS data that was collected by the Rand

Corporation from 2000 to 2002 (see [194] for more study information).[5] It is a sample of households in Los Angeles County California. The LAFANS is well suited for this project because it captures the travel behaviors of respondents' daily activities, including work, church, grocery store, school.[6] In 2000, Los Angeles county contained approximately 9 million people of which 45% are Latino, 31% White, 13% Asian, and 10% Black. The overall refusal rate for the sample was approximately 16% [196]. The data are a stratified random sample of households in Los Angeles County. The data are stratified by neighborhood poverty with an oversample of poor (60-89th percentile of poverty distribution) and very poor (top 10%) respondents. A total of 65 tracts were sampled: twenty tracts were allocated to both the poor and very poor stratum and 25 tracts were allocated to the non-poor (remaining 60% of poverty distribution). The data also oversample households with children under 18 by making them approximately 70% of the sample when they would have otherwise been 35%. Respondents were interviewed in person or on the phone and were allowed to take the survey in either English or Spanish. The sampling frame was solicited from 1990 census tracts. In wave 1, the project collected between 40-50 households from each of 65 Census tracts. There are total of 2777 households with a home Census tract. Not every household reported every activity location: 1518 households reported at least one work location, 2433 a grocery store, 945 a church, and 1324 have children in school. All summary statistics for the data are presented in Table 4.2.

### 4.2.1 Dependent Variables - Collective Efficacy, Informal Social Control, and Cohesion

I have three outcomes for this chapter: collective efficacy, informal social control, and cohesion. All outcomes are measured for each household, and the items were asked only of

[5] Link to L.A.FANS Documentation: http://lasurvey.rand.org

[6] I was also interested in examining the spatial distribution of day care locations. Day care locations were extremely rare in the data, and I did not proceed further with the analyses.

the main household respondent in the survey. Collective efficacy and the two dimensions, informal social control and cohesion were captured with measures that were almost identical to the Project on Human Development in Chicago Neighborhoods [188]. Cohesion and informal social control were measured on a 5-point Likert-scale. It was rescaled from 0 to 4 with higher values indicative of more of the construct (e.g. more collective efficacy). The questions are in Table 4.1. The collective efficacy measure is the mean of these ten questions. The alphas for the different measures are: .81 for collective efficacy, .71 for informal social control, and .73 for cohesion. Cohesion and informal social control are correlated at .54.

Table 4.1: Collective Efficacy, Cohesion, and Informal Social Control Questions

| Question | Construct |
|---|---|
| This is a close-knit neighborhood. | Cohesion : CE |
| There are adults kids can look up to. | Cohesion : CE |
| People are willing to help neighbors. | Cohesion : CE |
| Neighbors generally don't get along. (recoded) | Cohesion : CE |
| People in neighborhood don't share same values. (recoded) | Cohesion : CE |
| People in neighborhood can be trusted. | Cohesion : CE |
| Children skipping school and hanging out on street corner. | Informal Social Control : CE |
| Children were spray-painting graffiti on a local building. | Informal Social Control : CE |
| Children were showing disrespect to an adult. | Informal Social Control : CE |
| Adults watch out that kids are safe. | Informal Social Control : CE |

*Note: CE = Collective Efficacy*

Table 4.2: Summary Statistics

| | Mean | Std. Dev. |
|---|---|---|
| **Neighborhood Characteristics** | | |
| % Residential Land Use | 48.49 | 28.80 |
| % Industrial Land Use | 6.17 | 12.63 |
| % Retail Land Use | 4.49 | 6.71 |
| % School Land Use | 5.11 | 7.59 |
| % Office Land Use | 1.32 | 4.24 |
| % Other Land Use | 34.42 | 27.42 |
| Population Density | 15.17 | 11.06 |
| Ethnic Heterogeneity | 0.45 | 0.19 |
| % Poverty | 22.99 | 13.87 |
| Ave. Length of Residence | 9.25 | 2.80 |
| % Vacant Units | 4.85 | 3.62 |
| % Immigrants | 3.62 | 15.07 |
| **Household Characteristics** | | |
| Household Income (per 10k) | 3.97 | 4.58 |
| Residential Tenure (Years) | 7.28 | 8.89 |
| Homeowner(0/1) | 0.39 | 0.49 |
| Employed (0/1) | 0.64 | 0.48 |
| Own Car (0/1) | 0.75 | 0.43 |
| Married (0/1) | 0.56 | 0.50 |
| Have Kids (0/1) | 0.77 | 0.42 |
| Female (0/1) | 0.61 | 0.49 |
| Black (0/1) | 0.09 | 0.29 |
| Latino (0/1) | 0.57 | 0.50 |
| White (0/1) | 0.25 | 0.43 |
| Age (Years) | 41.24 | 13.70 |
| Distance to Work | 6.97 | 7.61 |
| Distance to Church | 3.02 | 3.87 |
| Distance to Grocery Store | 1.60 | 2.28 |
| Distance to Children's School | 1.99 | 4.36 |
| Collective Efficacy | 2.45 | 0.68 |
| Informal Social Control | 2.54 | 0.90 |
| Cohesion | 2.36 | 0.68 |

### 4.2.2 Independent Variables

#### Land Use

Land use data was obtained from the 2000 Southern California Association of Governments (SCAG). More details about the land use data are found in Appendix A. The data was initially in parcels, and it was apportioned to Census blocks by area and aggregated to Census tracts [16]. I created 6 categories of land use data: residential, industrial, retail, office, school, and other (e.g., parking, parks, agriculture, etc.). Each category represents the percent of some land use type in the Census tract.

#### Neighborhood Demographic Characteristics

The neighborhood characteristics are from 2000 Census Tracts. Population density is the number of people in the neighborhood divided by the area. Neighborhoods with more population density might be expected to have more interaction, and thus more collective efficacy. Racial/ethnic heterogeneity is measured with a Herfindahl index (Gibbs and Martin 1962: 670) of five racial/ethnic groupings (the groups are white, African-American, Latino, Asian, and other races), and takes the following form:

$$H = 1 - \sum_{j=1}^{J} G_j^2 \tag{4.1}$$

where $G$ represents the proportion of the population of racial/ethnic group $j$ out of $J$ groups. The economic resources of the tract were captured with the percent of residents in poverty.[7] As a measure of residential stability, I computed the average length of residence for residents. I used the percent vacant units to capture vacant housing units that are expected to reduce perceptions' collective efficacy. Given that immigrants may have a difficult experience establishing themselves in a new area and this may have negative

[7] The survey oversampled poor families. The percent in poverty is correlated with the percent families in the tract at .80.

consequences for neighborhood processes, I include a measure of the percent immigrants as the percent of foreign born residents out of all residents.

### Household Characteristics

Several household characteristics were measured with the LAFANS data, including household income, number of years living at a residence, whether or not someone was a homeowner, employed, owns a car, married, has children, respondent sex, respondent race and ethnicity, and age of respondent. Household income is per $10,000, and it is the sum of family earned income, asset income, and transfer income. Except for income, age, and years at residence, all of these characteristics are a series of indicator variables. The actual wording of questions is from the Census 2000.

### Physical Distance to Household Activities

Similar to last chapter, for each location, I computed a distance between the home and each of the four activity locations: work, school, grocery store, and church. These physical distances represent each household's spatial footprints. Distances were computed as the "crow flies" between tract centroids. I used Austin Nichols' vincenty program in Stata to compute these distances, which uses an ellipsoid model of the earth.[8] Some household's reported multiple activity locations (e.g. two jobs), and for these cases, I used the median distance of the set of distances.[9]

As suggested in the last chapter, one complication for computing distances between the home and activity locations are instances when the destination choice location is within the same Census tract. In this instance, the distance between home and the activity location in the same neighborhood is missing and undefined (since distance cannot be zero). To address this issue, I used the distance from the tract centroid to the nearest Census tract

[8]Another approach might use travel distance to account for the road network. The travel distance approach has been shown to produce approximately identical results to the"crow files" method [17].

[9]For example, if a respondent had a job 5 miles from their home and another job 10 miles from their home. The distance for this respondent would be 7.5 miles (the median of the two values).

boundary.[10]

### 4.2.3 Analytical Approach

This chapter uses structural equation models to examine households' perception of collective efficacy, informal social control, and cohesion. The missing data was assumed to be missing at random (MAR), rather then the more stringent assumption (MCAR). The models were estimated using full information maximum likelihood (FIML) to account for the missing data.[11] The standard errors are adjusted for the clustering of households in tracts. The models were checked with standard diagnostics, including multicollinearity and outliers. No collinearity issues were found, but households in one Census tract were removed from the analyses (N=16). Residents in this tract were traveling exceedingly far (approximately 300% farther) to all activities. All models were estimated in Stata 13.1 using the sem command. Given differences between the cohesion and informal social control dimensions of collective efficacy found in prior research [226], I present the results for collective efficacy generally as well as separately for each dimension.

## 4.3 Results

I begin by first briefly discussing the summary statistics for the distance measures. As can be seen in Table 4.2, the mean distance to work is 6.97 miles, church is 3.02 miles, grocery store is 1.6 miles, and children's school is 1.99 miles. Given the skew of this distribution, I also mention the median distances: 4.8 miles for work, 1.65 miles for church, .99 miles for store, and 1.01 miles for children's school. The size of these footprints exceeds most

[10] Another approach might generate random points within each Census tract and take the average distance between points. This process might be computed for multiple iterations/imputations. The result from this average 'random points' approach is expected to be approximately identical to the nearest boundary approach, but future research will want to test this possibility.

[11] I also created empirical Bayes measures for all of my outcomes [188]. These measures are somewhat akin to estimating the outcomes as latent variables from the structural equation modeling framework. The results were substantively similar.

conceptualizations of a neighborhood (i.e. a tract), but nonetheless, these values are not enormous.

When looking at the models in Table 4.3, we see a model for each outcome: collective efficacy, informal social control, and cohesion. The results are mostly similar across the different outcomes, and as a result, I discuss the results broadly as “collective efficacy”. As I note later though, some of the effects of the individual household characteristics differ across the models.

Starting with the spatial footprint distance measures, the results for the measures suggest that residents perceive more collective efficacy with their neighborhoods when their activities are located nearby their homes, rather than farther away.[12] There appears to be a clear unique distance decay effect for all activities, although the effects are quite modest in size. These effects are plotted in Figure 4.1, Figure 4.2, and Figure 4.3. Except for work, the plots cover 95% of the range of values in the data for each activity. While the substantive size of the effects was small, the strongest effects were distance to the grocery store for all outcomes.[13] The effect of distance to churches and grocery stores were slightly nonlinear. With all distances to all other activities at zero, a one standard deviation increase (approximately 2 miles) in distance to the grocery store, collective efficacy decreases by .14 standard deviations, holding all other measures constant. If distance to all four activities increases by 1 standard deviation, collective efficacy decreases .22 standard deviations, holding all of the other measures constant. Distance to church was slightly stronger for informal social control. A household’s distance to their children’s school had an impact on their perceptions of collective efficacy and informal social control, but not cohesion. The distance a household travels to work was not significantly associated with

[12] Although not shown, I also estimated models for households’ satisfaction with their neighborhood. The results were similar to the collective efficacy models. Most distant footprints patterns were associated with less satisfaction. One next step with this research is to examine whether collective efficacy is determined by or a determinate of neighborhood satisfaction. One approach might suggest that people coming together to solve a collection action problem might increase their satisfaction with their neighborhood, regardless of the outcome of the collective action problem.

[13] Nonetheless, the effect sizes were relatively comparable to other effects in the model (i.e. poverty).

any outcome.

When examining the household characteristics, we see that households with higher incomes and homeowners perceived significantly more collective efficacy in their neighborhood. On the other hand, employed respondents reported feeling less collectively efficacious with their neighborhood. Female respondents reported significantly less collective efficacy and informal social control than males. Latino residents perceived significantly more collective efficacy and informal social control than when compared to Asian and other race/ethnicity respondents. Older respondents perceived significantly more collective efficacy and cohesion.

Now examining the neighborhood demographic characteristics, we see that poverty is associated with significantly less collective efficacy. In fact, it is the strongest effect in the model, which is generally consistent with prior research at the neighborhood level [190]. For a one standard deviation increase in poverty, collective efficacy decreases by .35 standard deviations, holding all else constant.[14] Households with more vacant units in the neighborhood perceived significantly less collective efficacy and cohesion. Households in neighborhoods with more immigrants perceived significantly less cohesion.

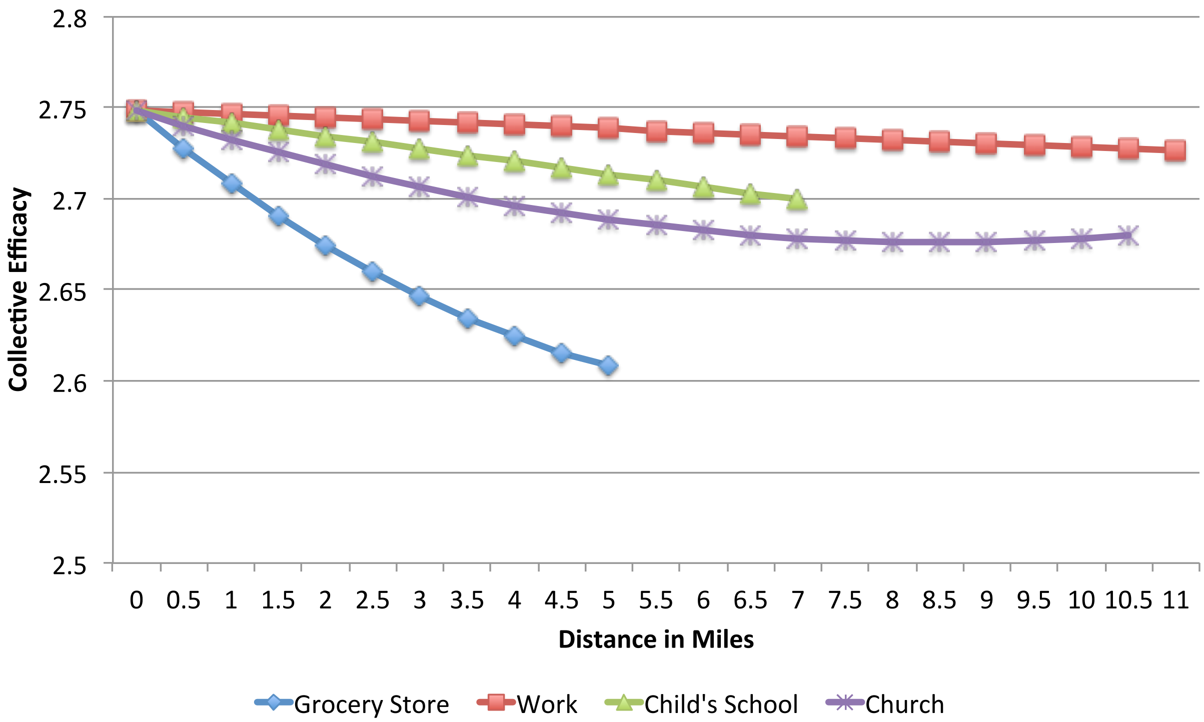
When looking at the land use characteristics, we see that when compared to the residential land use in the neighborhood, households in neighborhoods with more industrial area reported more collective efficacy. A one standard deviation increase in industrial land use when compared to residential land use leads to a .10 standard deviation increase in collective efficacy, with all else constant. Given the abundance of residential land use in most neighborhoods, we might attribute this finding to a "mixed" neighborhood containing both industrial and residential land use.[15] More "other" land use was also related to more

[14] I also estimated models with a nonlinear term for poverty (i.e., poverty squared). This term was significant for both outcomes, but the substantive size of this effect was quite small. After plotting the effect, it did not appear to have much substantive importance, and I removed it from the model.

[15] Another approach might suggest that the land use factors are mediated by the other distance measures in the model. To assess this possibility, I also estimated models without the distance measures in the model. The results were substantively similar for the land use and neighborhood measures.

collective efficacy.[16]

Figure 4.1: Households' Perception of Collective Efficacy




[16]Future research might more explicitly unpack the "other" category to assess what specifically is driving this finding. Prior research suggests that parks may be particularly important [41]. Religious institutions are another possibility.

Figure 4.2: Households' Perception of Informal Social Control

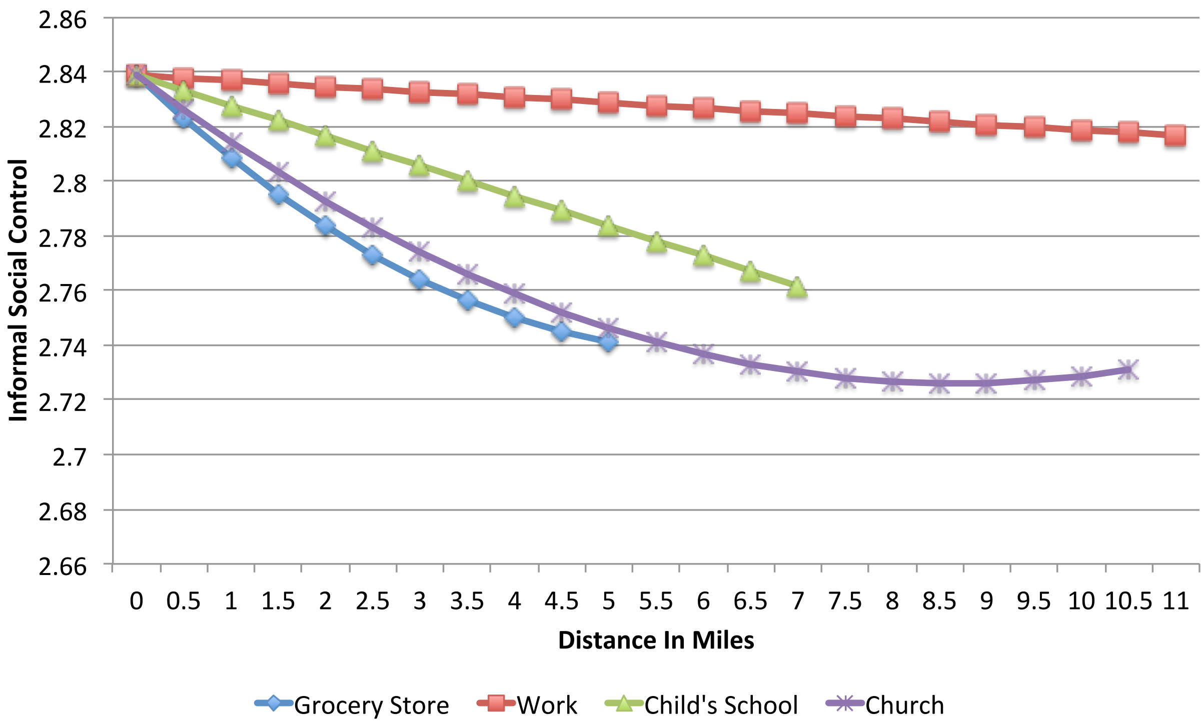


Table 4.3: Households' Perception of Collective Efficacy, Informal Social Control, Cohesion

| | Collective Efficacy | ISC | Cohesion |
|---|---|---|---|
| | Coef. | Coef. | Coef. |
| | (SE) | (SE) | (SE) |
| **Household Spatial Footprints** | | | |
| Distance to Work | -.002 | -.002 | -.002 |
| | (.0023) | (.0030) | (.0023) |
| Distance to Church | -.017 | -.026 + | -.010 |
| | (.0108) | (.0140) | (.0104) |
| Distance to Church * Distance to Church | .0010 ** | .0015 *** | .0006 * |
| | (.0003) | (.0004) | (.0003) |
| Distance to Store | -.043 * | -.033 | -.051 ** |
| | (.0195) | (.0236) | (.0198) |
| Distance to Store * Distance to Store | .0030 * | .0027 + | .0032 * |
| | (.0013) | (.0014) | (.0013) |
| Distance to School | -.007 * | -.011 * | -.002 |
| | (.0034) | (.0044) | (.0034) |
| **Household Characteristics** | | | |
| Household Income (per 10k) | .0142 ** | .0139 * | .0159 *** |
| | (.0043) | (.0058) | (.0039) |
| Homeowner (0/1) | .1165 *** | .1301 ** | .1133 ** |
| | (.0353) | (.0450) | (.0392) |
| Residential Tenure (Years) | -.001 | -.004 + | .0008 |
| | (.0017) | (.0026) | (.0017) |
| Employed (0/1) | -.042 | -.096 * | -.006 |
| | (.0274) | (.0429) | (.0272) |
| Own Car (0/1) | .0075 | .0397 | -.001 |

*Continued on next page*

Table 4.3 – *Continued from previous page*

| | Collective Efficacy | ISC | Cohesion |
|---|---|---|---|
| | Coef. | Coef. | Coef. |
| | (SE) | (SE) | (SE) |
| | (.0336) | (.0529) | (.0321) |
| Married (0/1) | .0314 | .0366 | .0222 |
| | (.0306) | (.0410) | (.0291) |
| Kids (0/1) | -.104 | -.111 | -.080 |
| | (.1022) | (.1600) | (.0652) |
| Female (0/1) | -.072 ** | -.108 ** | -.039 |
| | (.0273) | (.0408) | (.0270) |
| Black (0/1) | .1240 + | .1933 + | .0764 |
| | (.0720) | (.1070) | (.0601) |
| Latino (0/1) | .1315 * | .3241 *** | .0097 |
| | (.0566) | (.0745) | (.0572) |
| White (0/1) | .0910 | .1533 + | .0591 |
| | (.0590) | (.0794) | (.0564) |
| Age (Years) | .0029 ** | .0021 | .0036 ** |
| | (.0010) | (.0014) | (.0012) |
| **Neighborhood Demographic Characteristics** | | | |
| Population Density | .0047 | .0049 | .0052 |
| | (.0030) | (.0038) | (.0033) |
| Ethnic Heterogeneity | .0654 | .1004 | .0300 |
| | (.1050) | (.1399) | (.1024) |
| Poverty | -.017 *** | -.022 *** | -.014 *** |
| | (.0022) | (.0026) | (.0025) |

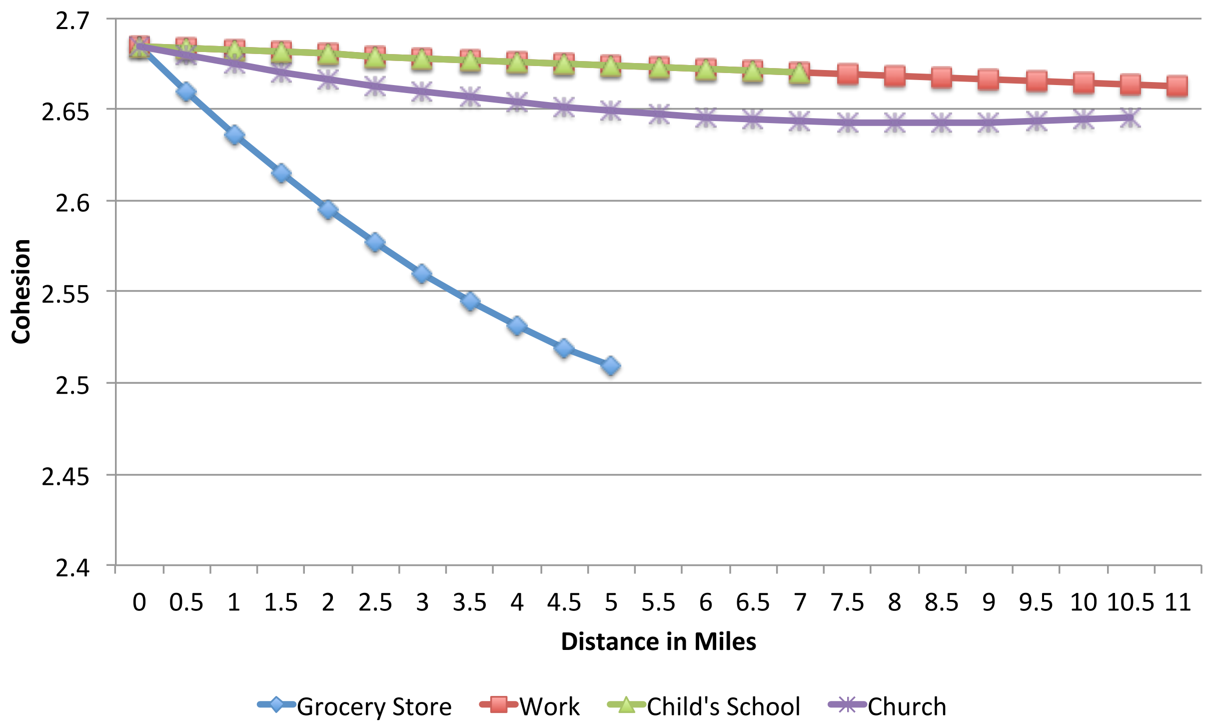
*Continued on next page*

Table 4.3 – *Continued from previous page*

| | Collective Efficacy | ISC | Cohesion |
|---|---|---|---|
| | Coef. | Coef. | Coef. |
| | (SE) | (SE) | (SE) |
| Ave Length of Residence (Years) | .0012 | -.010 | .0079 |
| | (.0063) | (.0087) | (.0065) |
| % Vacant Units | -.011 * | -.009 | -.012 * |
| | (.0056) | (.0070) | (.0053) |
| % Immigrants | -.004 + | -.003 | -.005 * |
| | (.0022) | (.0027) | (.0022) |
| **Neighborhood Land Uses** | | | |
| **Residential Land Use is Reference Group** | | | |
| % Retail Land Use | .0034 | .0027 | .0039 |
| | (.0026) | (.0036) | (.0024) |
| % Industrial Land Use | .0059 ** | .0067 ** | .0057 ** |
| | (.0018) | (.0023) | (.0020) |
| % Office Land use | .0039 | .0067 | .0006 |
| | (.0033) | (.0042) | (.0039) |
| % School Land Use | .0035 + | .0027 | .0037 * |
| | (.0021) | (.0031) | (.0018) |
| % Other Land Use | .0016 * | .0021 * | .0014 * |
| | (.0006) | (.0008) | (.0007) |
| Intercept | 2.770 *** | 2.982 *** | 2.585 *** |
| | (.2107) | (.2874) | (.1898) |
| R-Square | 0.21 | 0.13 | 0.23 |

*Note:* ISC = Informal Social Control. + = $p < .10$; * = $p < .05$; ** = $p < .01$; *** = $p < .001$

Figure 4.3: Households' Perception of Cohesion




## 4.4 Discussion

This chapter examined the impact of spatial footprint patterns on collective efficacy. While collective efficacy has received considerable attention in the neighborhoods literature, there is surprisingly little work on the characteristics that explain collective efficacy across the city. In tandem with a host of individual characteristics, I find that a variety of activity locations (i.e., church, grocery store, school) help to situate households' perception of collective efficacy in the community. The results from this chapter suggest that perceptions of collective efficacy are reduced when people travel farther for activities.

The spatial footprints of residents within and outside of the neighborhood over time may provide a basis for forming expectations about the neighborhood. One takeaway is that activities outside of the neighborhood have an impact on residents' home neighborhood. The findings suggest that different types of activities that are not directly linked to civic engagement and social ties are important for collective efficacy.

There are at least two explanations for this finding. One explanation suggests that spatial footprint patterns lead to more awareness of issues in the neighborhood. Information received at different activity locations may inform residents about problems in the neighborhood. Residents are arguably more likely to be coincident when nearby the home rather than farther away. As a result, residents might be more likely to run into each other and discuss issues about the neighborhood when nearby the home. Another explanation suggests that with more distant spatial footprints residents have fewer ties and less cohesion with the neighborhood. Prior research has suggested that more distant social ties are associated with residents perceiving less cohesion with their neighborhood [17]. When residents are located far from the home neighborhood for different activities, they might be less well connected with the issues ongoing in the neighborhood. Distinguishing between these different explanations is an interesting avenue for future research.

Focusing on the process of people's spatial footprints explicitly allows neighborhood researchers to put collective efficacy and other neighborhood processes into action. Even though the distances to various activities on average were not excessive and most activities were within a couple of miles, a main takeaway is that people do move around, and these movement patterns have consequences for neighborhood processes. While the neighborhoods literature often only uses a static conceptualization of residents' locations over time, the spatial footprint approach suggests a more fluid and opportunity contingent conceptualization of neighborhood processes (i.e., social control) that is situated within everyday life. The spatial footprint is an approach for incorporating how different people converge in space and time, and these colocation patterns may help to gauge the availability of resources, social influence, social control, and information sharing within and between neighborhoods.

Neighborhood researchers increasingly use smaller and smaller units of analysis (e.g. see [224]), and my findings suggest that these smaller units need to incorporate the spatial footprint patterns of residents. With a focus on small units of analysis such as street blocks or crime hot spots, research in this area implicitly suggests that the activities and explanations for crime are only a result of processes within these small units. The spatial footprint patterns of residents complicate this picture, suggesting that by exclusively focusing on using small units or crime hot spots, researchers might miss the broader activity patterns of residents and criminals alike.

Distance to stores was shown to have the strongest effect on residents' perception of collective efficacy in the neighborhood. Given that grocery stores were closer to home than the other activities, this might be expected. At the other end of the spectrum, distance to work had the farthest distance from the home and was not significant for any of the models. One explanation for these findings suggests a distinction for this particular type of activity. The distance to work is much farther on average when compared to other trips. This might simply just indicate that this activity is too far away to have a substantial impact on perceptions of the home neighborhood. Future research might examine the collective efficacy around work or other activity locations. Whereas this study focused on the collective efficacy of the home arguably where people are at night, this pattern does not necessarily offer insight into collective efficacy patterns over the day. It is also unclear what happens with resident's expectations for collective efficacy when outside of their neighborhood. Do these expectations matter when people are not nearby their homes for their willingness to intervene?

This study used a simple distance based measure to gauge spatial footprint patterns, and future research may want to test other possibilities. While I noted a few possibilities earlier in this dissertation, one possibility is to include measures of the area nearby activity locations. With this approach, future research might examine the characteristics nearby a grocery store location, and not just distance to the grocery store. On the other hand, as suggested in the last chapter, for many of the amenities, particularly grocery stores, we might expect for the characteristics nearby these activities to be largely similar to the home neighborhood. Future research might examine homophily preferences in spatial footprint patterns and how these relate to collective efficacy.

This study has limitations. Prior research has suggested that social ties might be important for collective efficacy patterns. This study followed almost all prior research and did not directly observe social ties. Nonetheless, I did capture the common neighborhood demographic characteristics, residential stability and ethnic heterogeneity, that are expected to foster social ties.[17] In addition, the land use characteristics might also be implicitly capturing social ties between residents. As suggested by Jacobs (1961), mixed land use fosters social interaction, and while the land use results were quite modest, the industrial land use finding might be suggestive of mixed land use effect. Second, prior work has suggested that crime is determined by and a determinate of collective efficacy. Future research might start to untangle these issues by examine collective efficacy patterns and crime over time. Third, it is unclear when people are actually using these different activities and with what frequency. Finally, this study did not directly include any measures of civic engagement, and future research will want to address this issue.[18]

When residents' spatial footprints are farther from the home neighborhood, they might be less involved, have less availability to be spatially present to address an issue, and have less knowledge of the activities of the home neighborhood. Approaching collective efficacy as a collective action problem, St. Jean (2007) notes that a challenge for this research is that many communities do not have collective action problems, are not organized in any particular way, and trust is often developed from a crime problem (i.e., collective efficacy results from crime). In other words, he suggests that residents may not be able to determine how neighbors might behave because many residents did not actively participate

[17]In future work, I might include the number of relatives and friends living in the neighborhood as reported by respondents. These are questions AB8_1 and AB8_2 in the LAFANS data. Spatial footprints might also predict resident's reports of social ties.

[18]Future research might address this issue by including the number of times respondents reported going to voluntary organizations (e.g. a neighborhood block organization). This variable is AB26 in the LAFANS data. Another set of models might test how distance to various spatial footprints impacts participation in a voluntary organization.

in solving a collective action problem [101].[19] This suggests three challenges for future research: 1.) Do residents actively participate in crime reducing strategies?, 2.) Do residents have knowledge (awareness) of other people participating in crime reducing strategies?, and 3.) How well do expectations and perception for action align with actual action? The modest effects from the various spatial footprint measures in this chapter suggest that households that have more spaced out activities perceive less collective efficacy in their neighborhood, and these activity patterns situate residents' perceptions for collective action in the neighborhood.

Whereas this chapter focuses on the impact of spatial footprints for collective efficacy, the following chapter takes the next step by examining how the spatial footprint relates to crime patterns in neighborhoods. With a focus on a resident's movement patterns in this chapter, the next chapter examines how the *population* of these movement patterns in the neighborhood has consequences for crime. As one example, this chapter demonstrated that the distance residents' travel to school impacts their perceptions of informal social control in the neighborhood. In the next chapter, I examine how the population of children going to school during the day and coming home from school later in the day relates to crime in neighborhoods.

[19] Residents from St. Jean's study expressed fear of retaliation as one of the driving factors for not becoming involved in a crime problem.

# Chapter 5

# The Spatial Footprint and Daily Crime Patterns: Situating Guardianship in 13 cities

## 5.1 Introduction

As shown empirically in the last two chapters, people's spatial footprints are not isolated within only one neighborhood, and different activities link people to different spaces of the city. As suggested in the second chapter, one consequence of spatial footprint patterns is that they will change the population density of different areas, and this change is expected to impact the amount of guardianship in the neighborhood because people need to be spatially and temporally *available* for crime control. In chapter 4, these spatial footprint patterns were associated with household's perceiving less collective efficacy in their neighborhood when residents were farther from the home, which suggests more crime in areas with more distant footprint patterns. In this last empirical chapter, I examine the impact of spatial footprint patterns on neighborhood crime.

The presence or absence of people likely serves as a powerful determinate for whether or not a crime occurs [42, 80]. Given that approximately 50% of crime in Los Angeles over the last decade occurred during the daytime, the spatial footprint of residents is fundamental to understanding crime patterns. Almost all of the research on neighborhoods and crime only focuses on residents' home location, capturing mainly the nighttime state of the neighborhood when most people sleep [20]. People's temporary location in areas outside of their home neighborhood (e.g., work or school location) and the interdependencies *between* different neighborhoods are a fundamental part of everyday life and must be considered when examining crime [19, 79, 76, 125].

Many disciplines frequently use residents' home neighborhoods as a proxy for their entire social lives, which ignores people's temporary spatial presence in other neighborhoods for activities such as work and school. Much research on neighborhoods and crime uses the "urban village" (i.e. within neighborhood) approach for understanding local crime. For decades, neighborhood theory and empirical work has bracketed each neighborhood, which isolates community processes within the focal area [229, 230]. By assuming a restricted spatial footprint of residents throughout the day, researchers, police, and policymakers are working under the assumption that the social and spatial criminogenic neighborhood processes are only the result of neighborhood residents and is the same at all times of day. To help fill this gap, this study creates a dynamic measure of neighborhoods that captures the spatial everyday travel patterns of people and uses these spatial footprints to understand local crime patterns over the day, week, and season.

Using data from 13 cities, in this chapter I examine how geographic space and time situate the activities of neighborhoods and the consequences of these patterns for crime. Specifically, this chapter examines the consequences for crime when people enter and exit neighborhoods for work and school throughout the day, week, and season. I compare this approach to the most common approach in the neighborhoods literature where people are assumed always in their nighttime home locations. I also examine how neighborhood crime patterns shift over different land uses, such as residential, commercial, school, and industrial areas, as they are occupied (or unoccupied) throughout the day, week, and season

### 5.1.1 Social Organization and Ties or Opportunity for Crime?

Whereas routine activities theory allows for the characteristics of neighborhoods to change over the day, social disorganization theory implies a much slower form of change over years and decades in the same spatial areas. The current project highlights these distinctions by using the spatial footprints of residents to gauge the activity of a neighborhood during the day and examining the consequences of these changes for crime. Social disorganization theory suggests a process where crime is restrained implicitly through residents having more social ties with other residents, and as a result, it is reasonable to suggest that in spaces where ties are maintained or activated, crime would be reduced. As one example, this implies that crime will be reduced on blocks that have restaurants because social ties are more likely formed, strengthened, and maintained in these spaces, which would be expected to increase social control. In this case, the occupants of the restaurant are local residents. Otherwise, if the occupants are people from outside the neighborhood, it is unclear and indeterminate for how social disorganization theory would suggest a process that would increase or decrease crime.

On the other hand, routine activities theory suggests that patterns of crime may change over the day due to variation in the combination of targets, offenders, and guardians. Using the example of a restaurant again, routine activities theory suggests that if crime is reduced in this neighborhood, this may be due to the increase in guardianship of occupants at the restaurant. Whereas routine activities theory focuses on the *presence* of guardians in the moment (i.e., a short-term process), social disorganization theory suggests a *longer-term* process through social networks. The social networks formed and maintained at the restaurant suggests increases in the potential for guardianship, and thus social disorganization theory is fundamentally a theory for why the guardians exist from routine activities theory. [1] Yet, we might expect crime to increase at restaurants since more people in the restaurant raises the possibility of more targets. Accordingly, if crime goes up, the effects of targets outweighs the effect of the increased guardianship to suggest a routine activities process. Crime would also be expected to increase if the number of offenders increased in the neighborhood, but there is not a clear theory or mechanism to suggest why

[1] This pattern suggests that both theories are operating through similar processes of social control (for examples see: [183, 186, 208]).

offenders would increase in an area that is not explicitly due to a target effect.[2]

Depending on the time of day, the social control of different spaces in the city will fluctuate as some areas of the city become excluded or activated through the daily shifting patterns of people's spatial footprints. Although rarely tested, this pattern suggests an approach that examines when an area is at risk for crime. As one example, much research has suggested the impact of alcohol outlets on criminal activity, but little research examines when these outlets are linked to crime. Presumably, an area of a city that has a bar will likely have little impact on crime during the day, and this effect will mostly occur in the evening. Using the restaurant again as an example, a restaurant will likely have most of its activity during the day and evening. This change in the activity of the restaurant or bar has consequences for the targets, guardians, and offenders. During the nighttime when the restaurant is closed, this suggests that the increased targets and guardianship from earlier in the day are now moved away from the local block. Accordingly, there is a rhythm of social control in neighborhoods over the day. If crime increased at night, this would suggest an effect of a lack of guardianship due to the loss of targets at the restaurant. While it might be reasonable to assume that offenders are more prevalent at night, it is unlikely that they would focus on restaurants given that there are no longer targets in the area. Bars, on the other hand, might have an increasing effect due to intoxicated patrons traveling home.

Drawing from social disorganization theory, the social control benefits from the ties at the restaurant may carry over to the nearby area via their spatial footprints. This would suggest a process where ties utilized in restaurants and bars would spread into the surrounding area, nearby the location of their homes and this would reduce crime. In this instance, the restaurant or bar might be considered a "third place" where residents come together outside of work and the home [160]. This implies that the effects from social disorganization theory would have a much broader spatial impact than just the local block.

[2]One process might suggest that offenders are increased in blocks when children are out of school and the school is nearby restaurants or on students spatial footprint home from school. These additional complications are left to future research.

On the other hand, routine activities theory suggests a spatially micro crime process since it focuses on the presence of people at the moment, and it is unclear how targets, guardians, and offenders in the surrounding area would impact crime on the focal block. While an agglomeration of restaurants in nearby blocks might suggest an increase in crime in the nearby area, it is not clear why this clustering of restaurants should increase crime in the focal block.

### 5.1.2 The Current Study

As an initial step to linking the spatial footprint to crime, I begin by comparing my approach that allows residents and crime to change over time to traditional neighborhood approaches where crime is the same at all times of day and residents are static and only located within their home neighborhood. I begin by discussing the data sources, and this follows into a discussion of measuring residents' spatial footprints. For this chapter, the locations of residents and one form of neighborhood change explicitly occurs when residents travel to and from their homes for work and school. Finally, I present the results, and discuss the implications for this chapter for neighborhood theory.

## 5.2 Data and Methods

This project uses data from several sources, and I discuss each source when discussing the measures. All data are from around 2010. Given that research suggests many social interactions occur in micro units [61, 69, 214, 216], the proposed study uses a census block as the unit of analysis. I use data from 13 cities listed in *Appendix A*, which is a total of 188,838 blocks.

### 5.2.1 Dependent Variables - Police Crime Data

The crime data are from city police departments. More details about the crime data are found in Appendix A. My six outcomes are Uniform Crime Report Part 1 crimes: homicide, aggravated assault, robbery, burglary, larceny, and motor vehicle theft.

### 5.2.2 Independent Variables

#### Land Use Data

From each of the cities with crime data, land use data was obtained from local county planning departments around 2010. More details about the land use data are found in Appendix A. All of the land use data are coded into parcels in the following categories: commercial/retail, industrial/manufacturing, white collar/office space, residential, schools, and other. For each category, a measure was created of the percent of the block area that is some land use type.

#### Business Data

To capture the business activity of the area, I use Mint global business data (also known as Orbis data). Although usually used for marketing and company report research, this database contains business information on over 100 million companies in 2012, including both public and private companies. Using unique 4 digit NAICS codes, data was obtained for the following businesses: bars, restaurants, and grocery stores.[3] The businesses locations were joined to 2010 census blocks. These measures are counts of the bars, restaurants, or grocery stores within the block.

[3]For further description of these data, see: http://mintglobal.bvdinfo.com.

### School Data

To measure where children are going to school during the day, I use 2009-2010 school year data from the National Center for Education Statistics. The Common Core data and the Private School Universe Survey cover all public and private schools in the US. These data contain the location of each school, along with each school's demographic characteristics, including age, race, number of children on free or reduced lunch, and total enrollment by grade. This information was summed and aggregated to census blocks. These data are for grades 1-12, and these data capture where children are located during schools hours. I also include a measure of the count of the number of schools within a block.

### Employee Data

The Longitudinal Employer Household Dynamics (LEHD) combines many sources of census data, and it contains information on where people live and where they work in 2010 Census blocks.[4] The LEHD contains information on all primary jobs (those with the highest wages), and thus each job only represents one person. The data is in 2010 census blocks, and it is broken up into residential location and work location characteristics. The residential characteristics are from the Statistical Administrative Research System (STARS) data, which combines federal administrative files, such as Social Security, IRS, Medicare, Medicaid, and Veteran's Affairs. The work locations are from Bureau of Labor Statistics (BLS) Quarterly Census of Employment and Wages (QCEW), Unemployment Insurance files, and other federal administrative records.

These data measure how many people *leave a neighborhood* for work, and *how many* people *come into the neighborhood* for work.[5] These files also contain information about worker characteristics of those entering and leaving the area, including race, age in three

[4] More information about LEHD data can be found here: http://lehd.did.census.gov/led/

[5] In order to ensure nondisclosure, the files are subject to minor thresholding: the block must have at least 5 persons residing in the block. LEHD also does not measure federal employees, railroad employees, or people who work at home (approximately 5% of U.S. population). Arguably the people who work from home do not leave the neighborhood over the day.

categories (16 to 29, 30 to 54, and 55 or older) and wage income in 3 categories (less than or equal to \$15,000 a year, between \$15,000-\$40,000 a year, and greater than \$40,000 a year).[6]

### Census and the American Community Survey

Several measures were created from the 2010 Census and the 5 year estimates of the 2007-2011 American Community Survey. To account for the housing in the area and given that research suggest vacancies lead to crime [104, 114, 184, 210, 217], I created a measure for the % vacant units within the block. I also created a measure for the % homeowners in the block. Drawing from social disorganization theory, the homeowners are expected to have a crime reducing effect due to more ties and neighborhood investment.

Using 2010 Census blocks, I create several measures of the total population (nighttime), the number of school age children, and the % young people age 16 to 29, given that these are the average age of most offenders. Racial/ethnic heterogeneity is measured with a Herfindahl index (Gibbs and Martin 1962: 670) of five racial/ethnic groupings (the groups are white, African-American, Latino, Asian, and other races), and takes the following form:

$$H = 1 - \sum_{j=1}^{J} G_j^2 \tag{5.1}$$

where $G$ represents the proportion of the population of racial/ethnic group $j$ out of $J$ groups. To account for the economic characteristics of the block, I use the proportion of low family income (less than \$30,000) residents. Given that this measure is only available in larger census units (e.g., block groups and tracts), these data were apportion from these larger units into blocks by population.[7]

[6] The race/ethnicity data contains information on the total number of respondents who are Hispanic or non-Hispanic. It also contains information on the number of whites, blacks, Asians, and other, but these groups are not cross tabulated by whether they are non-Hispanic or Hispanic. The number of non-Hispanics for each group (whites, blacks, Asian, and other) were assumed proportional to each group's representation in the block multiplied by the total number of non-Hispanics. These estimates were separate for residential locations of workers' characteristics and work locations of workers' characteristics.

[7] Using block groups, this measure was correlated with the percent in poverty at .80, which suggests substantial similarity.

### 5.2.3 Creating Time-Varying Measures and Analytical Plan

Given this is an initial exposition for understanding processes over the day, I compare 3 distinct sets of models:

1. *Yearly Models* - residents only in nighttime locations (i.e., home) and crime is averaged over years. This approach is the traditional baseline approach used in the neighborhoods literature.

2. *Nighttime Models* - residents only at nighttime locations (i.e., home), but crime changes over the day, week, and season.

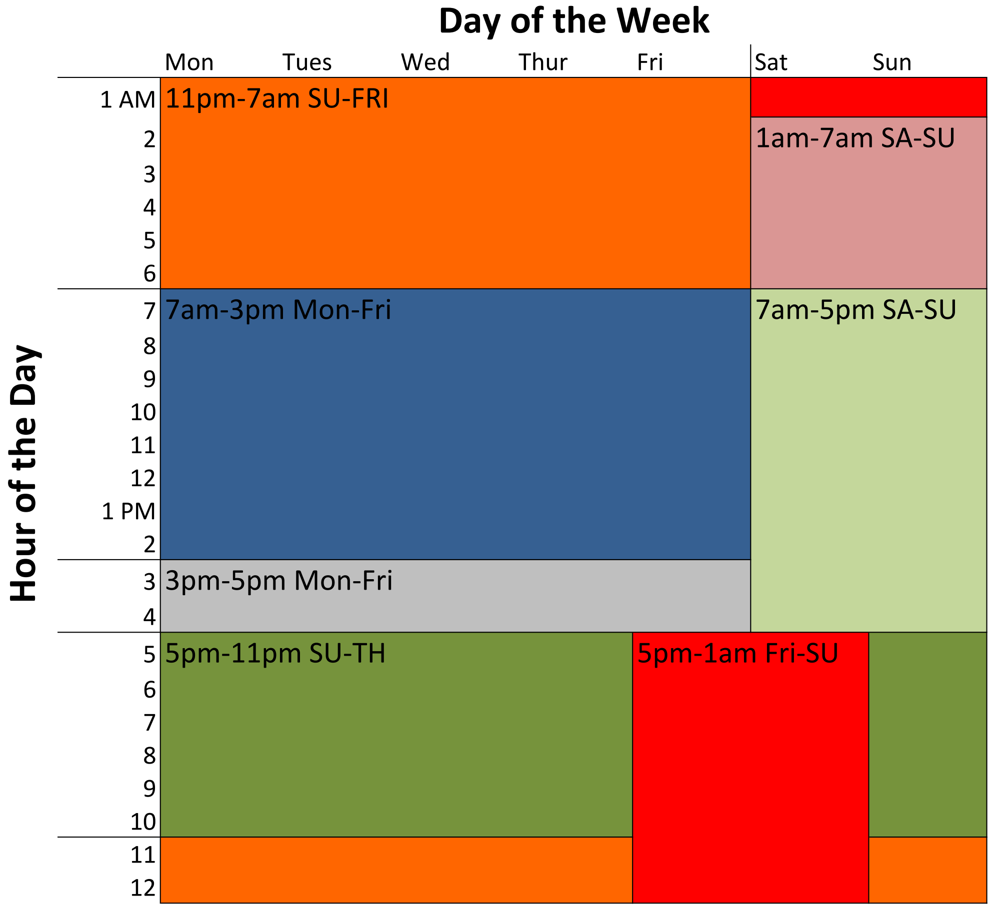
3. *Daytime and Nighttime Models* - residents travel to and from home, work, and school. Crime and the population measures change over the day, week, and season.

Each of the crime incidents has date and time information, and this allows for flexibly aggregating crime into different time intervals. It is fairly straightforward to compute the number of crimes for the nighttime location. In this approach, I simply sum the number of crimes over three years (2009-2011). To allow for crime to change over the day, I aggregate crime into different time intervals that are broken up for each season, time of day, and day of week. The four seasons are computed in 3-month intervals.[8] To capture time over the day and day of week, time intervals were computed for each of the 7 categories in *Figure 5.1*.[9] These time intervals correspond to various activity patterns, and this approach splits time into several theoretically motivated time intervals, including weekend vs. during the week, after school, during the work day, evening hours, late night, and leisure hours on weekend nights.

[8]The season and month combinations are: January, February, and December for Winter; March, April and May for Spring; June, July, and August for Summer; and September, October, November for Fall. I do not have measures for December 2008. None of the crime measures include crime data for December 2011.

[9]Other strategies for aggregating different time intervals are possible. Another approach would only aggregate crimes for each hour of the day for the entire year (or even each incident). There are also more potential time interval categories that might be important, including lunch hour. Yet, another approach would use the crime data (and crime type) to define the time interval categories as similar to latent class approaches. Given that this is an initial exportation into these issues, I leave these additional complications to future research.

Figure 5.1: Time Intervals for Fall, Winter, and Spring




*Note:* For summer, there is no 3pm-5pm Monday-Friday interval.
It is combined with the 7am-3pm Monday-Friday interval.

For the independent variables, the measures of *spaces* including different types of land uses and housing do not change over the day, week, or season, while the measures of *people* do change over time.[10] The population measures that change over time are population (logged+1), ethnic heterogeneity, % low-income, and % young people age 16 to 29. Given this is an initial exposition, I only focus on population changes due to shifts in the population due to work and school, and as a result, most of the time interval categories only use data from the nighttime (residential) locations.[11]

[10]Yet, by splitting crime into several time intervals, I test how the effect of the various covariates change over time (e.g., industrial areas at night).

[11]One possibility for future research is to test interactions between different time intervals and various measures. As one example, an interaction between alcohol outlets and the Friday and Saturday night time

As one example for capturing the neighborhood change during the day and after school, the population of the neighborhood during the week between 7am-3pm in the fall is represented as:

$$\textit{day population} = \textit{nighttime population} - \textit{people leaving} + \textit{people entering} \tag{5.2}$$

The nighttime population measures are straightforward to compute since they come directly from the census. The people *leaving* the block are comprised of the children going to school and employed/working people. The number of children *leaving* for school is from the 2010 census for children aged 6 to 17. The number of workers *leaving* is from the residential LEHD data, and it is counts of the of workers who live in block.[12] For the people *entering* the block, I again focus on school children and workers. The number of workers *entering* into a block to work is captured with the LEHD work data, which has information of where people work. The number of school children *entering* the block is captured with the education data on the locations of schools. This approach allows for teasing a part children and workers from the other occupants of the neighborhood during the hours when most children are at school and workers at their jobs. To capture the after school population of the neighborhood for this initial exposition, children are expected to all immediately return to their home block after school.[13]

Ethnic heterogeneity is measured with the same approach. Rather then capturing all population over the day, I compute measures for each race and then compute ethnic heterogeneity. The % young people throughout the day are captured with the ages of

intervals would explicitly capture when bars are most at risk for criminal activity. Although not explicitly used in this study, this approach is complementary to other work on risk terrain modeling and crime [37].

[12]The estimates for the number of people in a neighborhood might be improved by incorporating information on the time of day when people leave for work. I leave this additional complication for future work. In addition, for approximately 1% of blocks, the population of the block was negative, and these cases were rounded to zero.

[13]This assumption could be tested by uniformly placing children between home and school locations. I leave this additional complication to future research. This approach necessarily implies a focus on where different ages/grades of children are located, rather than just the population turnover in an area over the day. Another approach would use friendship networks of children in schools to estimate where children are located after school.

workers aged 16 to 29 and children in school ages 16-17. Finally, the % low-income captures the proportion of residents that are low-income in the block.[14] Low-income workers are again computed using the LEHD data in combination with the school data. Low-income school children entering the neighborhood was measured with the number of students on the free lunch program.[15] The summary statistics are presented in Table 5.1.

Table 5.1: Summary Statistics

| | Daytime | | After School | | Nighttime | |
|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD |
| % Industrial LU | 3.90 | 16.31 | 3.90 | 16.31 | 3.90 | 16.31 |
| % Residential LU | 56.21 | 44.36 | 56.21 | 44.36 | 56.21 | 44.36 |
| % Retail LU | 5.12 | 17.38 | 5.12 | 17.38 | 5.12 | 17.38 |
| % Office LU | 1.80 | 10.27 | 1.80 | 10.27 | 1.80 | 10.27 |
| % School LU | 1.55 | 10.78 | 1.55 | 10.78 | 1.55 | 10.78 |
| # of bars | 0.01 | 0.13 | 0.01 | 0.13 | 0.01 | 0.13 |
| # of grocery stores | 0.03 | 0.20 | 0.03 | 0.20 | 0.03 | 0.20 |
| # of restaurants | 0.13 | 0.57 | 0.13 | 0.57 | 0.13 | 0.57 |
| % Homeowners | 58.46 | 32.47 | 58.46 | 32.47 | 58.46 | 32.47 |
| % Vacant Units | 9.99 | 14.02 | 9.99 | 14.02 | 9.99 | 14.02 |
| Logged Population | 81.73 | 381.39 | 80.35 | 362.33 | 70.72 | 134.01 |
| % Young People | 19.94 | 19.33 | 19.82 | 17.96 | 17.48 | 13.91 |
| Ethnic Heterogeneity | 36.77 | 22.71 | 36.68 | 22.73 | 29.82 | 24.32 |
| % Low-income | 25.31 | 26.47 | 29.31 | 27.04 | 26.73 | 20.88 |

*Note:* SD = Standard Deviation, LU = Land Use Area

I calculated spatial lags of all of variables by using a 2.5-mile inverse distance decay function (in which block groups more than two and half miles away have weights of zero in the "W matrix").[16] The spatial weights matrix is row standardized. All of the spatial lags include information from neighborhoods that are outside the city boundary since it is well

[14]The LEHD data only contains information on wages from primary jobs, while the ACS contains information on family and household income. To make income and wages comparable, I computed the proportion of low-income LEHD jobs with low wages (< $15,000 a year). I than compared this proportion with various thresholds for the proportion of low-income residents using family income. The proportion of low-income residents within the block using a threshold of family income at $30,000 was comparable to the number of residents who work low-income jobs.

[15]Information on free lunch is only available for public school students. This information is not available for private school students, although it is unlikely that free lunch programs is of much consequence for private schools.

[16]The results were similar when using a 5 mile distance decay as well. I also employed a bi-weight kernel approach, and the results were similar.

known that the estimates might be biased when only including information within cities [234].[17]

As an analytical approach, I use fixed effects count models. Given that excessive variation is often present in the crime counts, I use a negative binomial model when appropriate.[18] To examine crime patterns during a particular time of day and day of week, models were estimated for each time interval category for each of my six crime outcomes. A general expression of the models that change over the day, week, and season is:

$$y_q = \alpha + \beta_2 TI + \beta_3 C + \Gamma LU_g + \Gamma X + \rho WZ \tag{5.3}$$

where $q$ is the time interval coding scheme, $\alpha$ is an intercept term, $TI$ is a vector of Q-1 indicator variables for capturing each time interval $Q$ (e.g. one interval would be Fall 3pm-5pm Monday-Friday), $\beta_2$ is a vector of each time interval's effect on the crime rate, $C$ is a vector of *J-1* indicator variables for $J$ cities, $\beta_3$ is vector of each city's effect on crime rate, $LU_g$ is a vector of the proportion of the block of land use $g$ of *G-1* land use types, $\Gamma$ is vector of the impact of these land use variables, $X$ is a vector of neighborhood variables such as demographics and activity variables with $\Gamma$ effects, $\rho$ is the impact of a vector of spatially weighted variables of the nearby area, and $W$ is the spatial weights matrix for a vector of $Z$ variables, such as land use and demographics.[19] The fixed effects for each city eliminate between city variation.[20] The series of different time interval fixed effects allows

[17] Although not employed in this chapter, as I noted in the 2nd and 3rd chapters, the spatial footprint allows for more explicit theoretical and empirical development of the "W matrix". As discussed in the discussion of chapter 3, future work might more explicitly incorporate various spatial footprint strategies to identify the nearby area.

[18] Decomposing a relatively rare event, such as homicide into time intervals resulted in some estimation issues, and as a result logistic regressions were used for these models.

[19] Some blocks have people in them during the day, but do not have any residents at night. It is also possible but quite rare for some blocks to have a daytime population of zero when everyone leaves during the day. When this occurred, I imputed a zero for these blocks. The *nightly* and *day and night* models also contain an indicator to control for this effect in the models.

[20] I do not estimate random effects multilevel models because I am not explicitly interested in examining the variation in these different cities, only neighborhoods, and the fixed effects model allows for a more conservative test. In addition, my sample is a convenience sample of cities and the results would only be representative of the cities in my study.

for comparisons only within specific times of day, day of week, and season of the year.[21] There was no evidence of collinearity problems or influential observations.[22] For the models with crime in different time intervals, the total number of hours within a time interval is in all of the models as offsets (log transformed, with the coefficient constrained to 1) to effectively transform the dependent variables into crime rates per hour.[23]

## 5.3 Results

### 5.3.1 Neighborhood Demographics and Land Uses over the Day

Before turning to the crime results, as a proof of concept for the population at different times of day, Tables 5.2, 5.3, 5.4, and 5.5 show the correlations of various neighborhood characteristics at three different time intervals that are based on different activity patterns: daytime (7am-3pm Monday-Friday in the Winter), after school (3-5pm Monday-Friday in the Winter), and nighttime (after 5 pm Monday -Friday in the Winter). For example, row 2 in column 1 in Table 5.2 shows that there is a .95 correlation between after school population of a neighborhood and the population of the neighborhood during the daytime. Even with only focusing on the location of students and employees, we see that the population of different areas substantially fluctuates throughout the day. The correlation

[21] Additional model specifications are possible for future research. One approach would examine a series of interactions between land uses, population variables, and time intervals. For example, crime may increase when children are not in school during the daytime of summer months in residential areas, and this would be captured by an interaction between residential land use and a summer time interval indicator (June/July/August 8am-5pm Mon-Fri). On the other hand, crime may decease by having more guardians in the neighborhood when others are at work. Another interaction that could be tested is between school land use and a spring time interval (March/April/May 3pm-5pm Mon-Fri), which would capture the area directly around the school after school during school months. In all of these examples, the interactions effectively test how different spaces of the city are moderated by different times of day, day of week, season to impact crime. Other non-linear specifications are also possible. These complications are left for future work.

[22] To test for spatial autocorrelation, I use a Moran's I, and no issues were found. The results indicated that the Moran's I varied a bit over the day, day of week, and season, but the size of the Moran's I was quite small and rarely significant.

[23] See [18] for other possibilities for the denominator for different crime rates.

Table 5.2: Correlations for Population over the day in the fall

| | Daytime | After School | Nighttime |
|---|---|---|---|
| Daytime | 1 | | |
| After School | .95 | 1 | |
| Nighttime | .25 | .30 | 1 |

Table 5.3: Correlations for % Young People (Age 5 to 18) over the day

| | Daytime | After School | Nighttime |
|---|---|---|---|
| Daytime | 1 | | |
| After School | .93 | 1 | |
| Nighttime | .45 | .46 | 1 |

between nighttime and daytime is only .25. The spatial footprints between different areas changes the population of different neighborhoods. Whereas population shows the greatest instability, the highest correlations were shown for poverty across the day to suggest stability. The distribution of residents living in poverty is fairly constant over the day, yet there still is about .25 difference between the day and nighttime.

In Figure 5.2, I have graphed the correlations between population over the day and various land uses. As we can see, residential land uses are mostly populated at night when people are most likely at home, while other land uses are much more likely active during the day. Similar to the demographic characteristics, these patterns suggests that people are shifting around to different parts of the city over the day, and many land use characteristics are "active" and busy at different times of day.

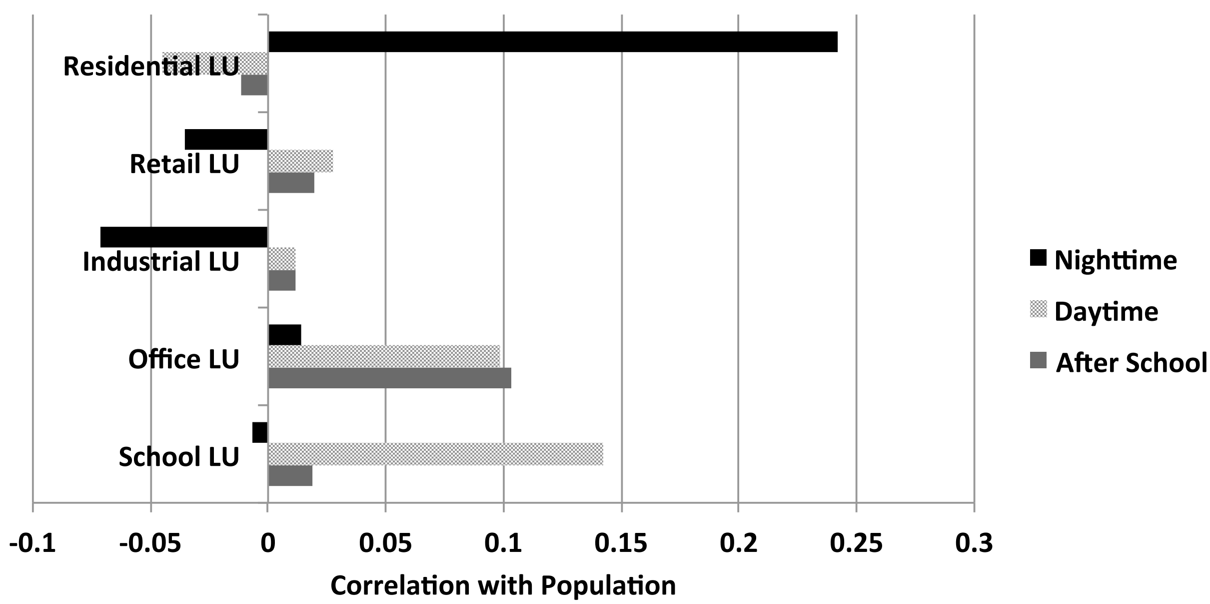
Table 5.4: Correlations for Ethnic Heterogeneity over the day

| | Daytime | After School | Nighttime |
|---|---|---|---|
| Daytime | 1 | | |
| After School | .98 | 1 | |
| Nighttime | .65 | .66 | 1 |

Table 5.5: Correlations for % Poverty over the day

| | Daytime | After School | Nighttime |
|---|---|---|---|
| Daytime | 1 | | |
| After School | .89 | 1 | |
| Nighttime | .75 | .89 | 1 |

Figure 5.2: Correlations with Population and Land Use



### 5.3.2 Violent Crime Models

Now turning to the crime models, as I mentioned earlier I focus on three sets of models for each of the six crime outcomes: 1) baseline neighborhood models with no resident or crime change and everything is averaged over the year (noted as *Yearly* in the tables), 2) crime changes over the day, week, and season, but population is only at home location (noted as *Nightly* in the tables), 3) residents and crime change over the day, week, and season (noted as *Day and Night* in the tables). Although not discussed in this section, *Appendix D* and *Appendix E* have all of the models estimated separately for each city and time of day, day of week, and season (each time interval). Given the other chapters focus on Los Angeles, in *Appendix F*, I also include models for only Los Angeles that are broken out for each time interval of the day.

I begin with the results for the violent crime models for aggravated assault, robbery, and homicide in Table 5.6. When examining the effects of various land uses on the focal block, residential areas are consistently associated with lower violent crime rates in all of the models, while retail areas are always associated with higher violent crime rates. Industrial areas are shown to have no effect for the yearly models for assaults and homicides, but industrial areas are significant for robberies. By incorporating information on different times of day, industrial areas significantly reduce violent crime on the focal block for assaults and robberies. The effect approximately doubles when accounting for the time of day. Office spaces are shown to have increasing or no effect for violent crime for the yearly models with people only in nighttime locations. When allowing people to move around during the day, office areas and robberies both are associated with crime reductions. The sign for offices flips for robberies when looking at the three sets of models. When examining the spatial lags that capture the nearby area around blocks, we see that almost all types of land use areas are associated with more violent crime when compared to all other land use areas. On the other hand, focal blocks with more offices nearby have less violent crime.

Blocks with schools suggest a pattern with more assaults, although this effect is reduced when accounting for change over the day. The sign actually flips for the effect of school land use over the day for robberies (from positive to negative). As I note below, the effect for young people is now positive and significant for robberies. This suggests the population moving around during different hours of the day, week, and season helps to separate the effects of different spaces and the people within them.

More businesses including bars, restaurants, and grocery stores on the focal block are all associated with more crime. When examining the nearby area with the spatial lags, more bars in the area are again associated with more assaults and robberies, while more grocery stores and restaurants are associated with reductions in criminal activity in the focal block. This pattern suggests an important effect for spatial scale where the benefits of restaurants and grocery stores for forming and maintaing ties carries over into the nearby area, while the opportunity for crime is more concentrated on the focal block.

There is also evidence of more vacancies being consistently associated with more violent crime on the focal block, and more violence in the focal block when vacancies are nearby. More homeowners are always associated with less violent crime on the block. The presence of homeowners nearby the focal block are suggestive of a process where homeowners reduce robberies, but actually increase assaults and homicides.

Turning to the measures that change over the day, we see that more population and more low-income people in the focal block and nearby area are always associated with more assaults, robberies, and homicides. These effects are slightly reduced when capturing the day and night movement patterns. The ethnic/racial heterogeneity of the focal block and nearby area has mixed effects in all of the different models. More ethnic heterogeneity in the focal block is consistently associated with less homicide. More heterogeneity in the nearby area is associated with less assaults, but more robberies, and nil effects for homicides. The % young people on the block are associated with more robberies over the day (the sign flips from the other models), but less assaults. When examine the effects of young people in the surrounding area, we again see that their sign flips for assaults and robberies. More young people in the nearby area is associated with more assaults and robberies when looking at the yearly models, but these effects are no longer significant when looking at crime over the day.

### 5.3.3 Property Crime Models

The results of the property crime models for larceny, motor vehicle theft, and burglary are shown in Table 5.7. For the land use measures in the focal block, we again see that residential areas are associated with less property crime, while retail areas are associated with more property crime. Whereas the violent crime models suggested a protective effect of industrial and office areas, we see that for property crimes these areas are associated with more crime. One notable exception is the % office for motor theft when accounting for spatial footprint turnover during the day, the sign flips to negative in the day and night models.

We also previously saw schools being associated with more assaults, but we now see them associated with more larcenies. This seems reasonable given that other crime types may be much less prevalent on school grounds. On the other hand, school areas appear to have a protective effect for robberies, homicides, motor vehicle thefts, and burglaries. The effect of schools across these models also flips from positive to negative, which is suggestive of the time of day measures being important for specifying these models. For example, when examining the yearly models, school areas are expected to increase burglaries, but in the model incorporating time of day information they reduce burglaries. In addition, the effect for young people is now significant in the time of day model for larcenies. This suggests that the positive effect for the yearly model captures both the school land use and the children at the school, but when parsed out over the day, we see a protective effect for school areas, but increased burglaries likely due to the concentration of young people.

The pattern of results for businesses are also similar to the violent crime models with more of these entities on the focal block being associated with more property crime. The effects for the nearby area are also similar to the violent crime models, except for larceny. Restaurants in the nearby area show evidence of an increase in larcenies in the focal block. This pattern of results suggests that opportunities on a small spatial scale in the focal block are associated with more opportunity for crime, while the spatial scale of the benefits of social ties are likely a broader area and may in fact carry over into the nearby area.

Homeowners and vacancies have similar effects to the violent crime models. Again we see that homeowners in the focal block and nearby area are generally associated with a protective effect, while vacancies are always associated with more property crime.

The effects of population are similar to the violent crime models: more population is associated with more property crime. More population in the nearby area is associated with more motor thefts, but population has a protective effect for larcenies and burglaries. We also see that by incorporating time of day information, the models appear to be specified better. For example, the effect for low-income residents and young people in the focal block both show the sign of the effect flipping for larcenies to the expected effect. These effects also become significant for burglaries as well. More low-income residents in the surrounding area are all consistently associated with more burglaries, larcenies, and motor vehicle thefts. As expected more young people in the nearby area are associated with more larcenies, motor vehicle thefts, and burglaries, which is suggestive of a micro opportunity effect. More ethnically/racially heterogeneous blocks are associated with more property crimes. When examining the effect of the racial/ethnic heterogeneity of the surrounding area, we see that ethnic heterogeneity has a protective effect. This pattern is suggestive of heterogenous areas surrounded by homogenous areas as having the most property crime, which also suggests the importance of the spatial scale for heterogeneity.

Table 5.6: Violent Crime Models

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | -0.0005 | -0.0004 | -0.0020*** | -0.0018** | -0.0015*** | -0.0030*** | 0.001 | 0.0009 | -0.0004 |
| % Residential LU | -0.0088*** | -0.0075*** | -0.0065*** | -0.0127*** | -0.0113*** | -0.0103*** | -0.0074*** | -0.0070*** | -0.0062*** |
| % Retail LU | 0.0089*** | 0.0079*** | 0.0067*** | 0.0160*** | 0.0124*** | 0.0114*** | 0.0055*** | 0.0047** | 0.0036* |
| % Office LU | -0.0009 | -0.0013* | -0.0029*** | 0.0021* | 0.0004 | -0.0010* | -0.0044 | -0.0022 | -0.0031 |
| % School LU | 0.0091*** | 0.0076*** | 0.0019*** | 0.0032*** | 0.0025*** | -0.0007* | -0.0009 | -0.0007 | -0.0053* |
| # of bars | 0.4333*** | 0.3354*** | 0.3322*** | 0.2384*** | 0.1675*** | 0.1593*** | 0.3052** | 0.3554*** | 0.3322*** |
| # of grocery stores | 0.2772*** | 0.2336*** | 0.2486*** | 0.5296*** | 0.4200*** | 0.4294*** | 0.1587** | 0.1424** | 0.1555** |
| # of restaurants | 0.1661*** | 0.1271*** | 0.1149*** | 0.2640*** | 0.1912*** | 0.1768*** | 0.0850** | 0.0774*** | 0.0667** |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.0103*** | -0.0099*** | -0.0102*** | -0.0073*** | -0.0071*** | -0.0072*** | -0.0077*** | -0.0077*** | -0.0084*** |
| % Vacant Units | 0.0092*** | 0.0092*** | 0.0091*** | 0.0083*** | 0.0086*** | 0.0085*** | 0.0117*** | 0.0117*** | 0.0112*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.5563*** | 0.5781*** | 0.5428*** | 0.4869*** | 0.4864*** | 0.4613*** | 0.6012*** | 0.5923*** | 0.5586*** |
| % Young People | -0.0019*** | -0.0038*** | -0.0008** | -0.0001 | -0.0009** | 0.0012*** | 0.0013 | 0.0013 | 0.0029 |
| Ethnic Heterogeneity | -0.0002 | -0.0006** | -0.0004 | -0.0001 | -0.0003 | 0.0002 | -0.0041*** | -0.0044*** | -0.0043*** |
| % Low-income | 0.0046*** | 0.0040*** | 0.0043*** | 0.0026*** | 0.0020*** | 0.0026*** | 0.0059*** | 0.0064*** | 0.0054*** |

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Table 5.6 – *Continued from previous page*

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.0101*** | 0.0082*** | 0.0110*** | 0.0162*** | 0.0131*** | 0.0161*** | 0.0187*** | 0.0182*** | 0.0195*** |
| % Residential LU | 0.0079*** | 0.0075*** | 0.0052*** | 0.0199*** | 0.0200*** | 0.0185*** | 0.0102*** | 0.0099*** | 0.0091*** |
| % Retail LU | 0.0131*** | 0.0121*** | 0.0121*** | 0.0233*** | 0.0238*** | 0.0245*** | 0.0168** | 0.0194*** | 0.0193*** |
| % Office LU | -0.0532*** | -0.0611*** | -0.0627*** | -0.0567*** | -0.0573*** | -0.0600*** | -0.0281 | -0.0327* | -0.0330* |
| % School LU | 0.0078* | 0.0092*** | 0.0253*** | 0.0073 | -0.0017 | 0.0106*** | 0.0007 | 0.0054 | 0.0119 |
| # of bars | 0.0025*** | 0.0033*** | 0.0030*** | 0.0017*** | 0.0025*** | 0.0022*** | 0.0004 | -0.0002 | -0.0007 |
| # of grocery stores | -0.0019*** | -0.0017*** | -0.0011*** | -0.0026*** | -0.0023*** | -0.0014*** | 0.0009 | 0.0006 | 0.001 |
| # of restaurants | -0.0004*** | -0.0005*** | -0.0006*** | 0.0003*** | 0.0001* | 0.0001 | -0.0016*** | -0.0013*** | -0.0014*** |
| **Housing** | | | | | | | | | |
| % Homeowners | 0.0172*** | 0.0156*** | 0.0106*** | 0.0017* | 0.0012* | -0.0032*** | 0.0104** | 0.0097** | 0.0069* |
| % Vacant Units | 0.0423*** | 0.0372*** | 0.0423*** | 0.0383*** | 0.0276*** | 0.0332*** | 0.0572*** | 0.0506*** | 0.0526*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.0861** | 0.0326 | 0.0717*** | 0.1153*** | 0.0874*** | 0.0637*** | 0.2114 | 0.1725 | 0.1773* |
| % Young People | 0.0132*** | 0.0101*** | -0.0014 | 0.0071*** | 0.0048*** | -0.0011 | -0.0064 | -0.0105 | -0.0153* |
| Ethnic Heterogeneity | 0.0007 | 0.0011*** | 0.0007* | -0.0029*** | -0.0028*** | -0.0030*** | <.0001 | 0.0014 | 0.0008 |
| % Low-income | 0.0484*** | 0.0470*** | 0.0405*** | 0.0431*** | 0.0431*** | 0.0368*** | 0.0416*** | 0.0409*** | 0.0396*** |
| Intercept | -5.6399*** | -15.5433*** | -16.1343*** | -5.5242*** | -15.7068*** | -16.0789*** | -10.7256*** | -20.9954*** | -20.9890*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. These models also include an indicator for blocks that had zero population during a time interval. The 'yearly' models also include city fixed effects. These effects are not included in the table for parsimony. The table is unstandardized coefficients.*

Table 5.7: Property Crime Models

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.0055*** | 0.0048*** | 0.0024*** | 0.0079*** | 0.0070*** | 0.0045*** | 0.0068*** | 0.0059*** | 0.0026*** |
| % Residential LU | -0.0110*** | -0.0101*** | -0.0087*** | -0.0070*** | -0.0060*** | -0.0046*** | -0.0038*** | -0.0036*** | -0.0022*** |
| % Retail LU | 0.0137*** | 0.0135*** | 0.0120*** | 0.0061*** | 0.0055*** | 0.0041*** | 0.0067*** | 0.0063*** | 0.0038*** |
| % Office LU | 0.0061*** | 0.0043*** | 0.0019*** | 0.001 | 0.0004 | -0.0013*** | 0.0048*** | 0.0037*** | 0.0012*** |
| % School LU | 0.0067*** | 0.0052*** | 0.0007** | 0.0012* | 0.0003 | -0.0041*** | 0.0043*** | 0.0035*** | -0.0010*** |
| # of bars | 0.2882*** | 0.2635*** | 0.2628*** | 0.2935*** | 0.1962*** | 0.1847*** | 0.1252*** | 0.1133*** | 0.1147*** |
| # of grocery stores | 0.4077*** | 0.3665*** | 0.3691*** | 0.1313*** | 0.1059*** | 0.1201*** | 0.1316*** | 0.1319*** | 0.1667*** |
| # of restaurants | 0.2642*** | 0.2285*** | 0.2123*** | 0.1451*** | 0.1180*** | 0.1053*** | 0.1544*** | 0.1359*** | 0.1405*** |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.0040*** | -0.0034*** | -0.0032*** | -0.0066*** | -0.0062*** | -0.0066*** | -0.0029*** | -0.0025*** | -0.0037*** |
| % Vacant Units | 0.0048*** | 0.0055*** | 0.0057*** | 0.0034*** | 0.0042*** | 0.0041*** | 0.0093*** | 0.0103*** | 0.0098*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.5367*** | 0.5505*** | 0.5379*** | 0.5828*** | 0.6362*** | 0.5985*** | 0.5778*** | 0.6101*** | 0.5162*** |
| % Young People | <0.0001 | <0.0001 | 0.0019*** | 0.0024*** | 0.0024*** | 0.0039*** | 0.0009** | 0.0012*** | 0.0013*** |
| Ethnic Heterogeneity | 0.0010*** | 0.0017*** | 0.0024*** | 0.0006** | 0.0004* | 0.0010*** | 0.0019*** | 0.0024*** | 0.0020*** |
| % Low-income | -0.0008*** | -0.0008*** | 0.0005*** | 0.0002 | -0.0003 | 0.00001 | 0.00001 | 0.0005*** | 0.0009*** |

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Table 5.7 – *Continued from previous page*

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.0061*** | 0.0065*** | 0.0065*** | 0.0107*** | 0.0085*** | 0.0083*** | -0.001 | -0.0026*** | -0.0006 |
| % Residential LU | 0.0116*** | 0.0117*** | 0.0107*** | 0.0057*** | 0.0053*** | 0.0061*** | 0.0135*** | 0.0123*** | 0.0114*** |
| % Retail LU | 0.0202*** | 0.0190*** | 0.0179*** | 0.0107*** | 0.0115*** | 0.0119*** | 0.0176*** | 0.0167*** | 0.0167*** |
| % Office LU | -0.0223*** | -0.0287*** | -0.0282*** | -0.0349*** | -0.0340*** | -0.0360*** | -0.0026 | -0.0044** | -0.0063*** |
| % School LU | 0.0015 | -0.0039*** | 0.0030** | -0.0224*** | -0.0246*** | -0.0206*** | 0.0007 | 0.002 | 0.0109*** |
| # of bars | 0.0024*** | 0.0028*** | 0.0030*** | 0.0023*** | 0.0026*** | 0.0025*** | 0.0044*** | 0.0044*** | 0.0037*** |
| # of grocery stores | -0.0034*** | -0.0036*** | -0.0033*** | -0.0023*** | -0.0023*** | -0.0019*** | -0.0029*** | -0.0025*** | -0.0022*** |
| # of restaurants | 0.0006*** | 0.0006*** | 0.0006*** | -0.0009*** | -0.0010*** | -0.0009*** | -0.0007*** | -0.0008*** | -0.0007*** |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.0030*** | -0.0025*** | -0.0032*** | -0.0015* | -0.0006 | -0.0010* | -0.0009 | -0.0013*** | -0.0034*** |
| % Vacant Units | 0.0449*** | 0.0443*** | 0.0446*** | 0.0064*** | 0.0064*** | 0.0014 | 0.0326*** | 0.0271*** | 0.0276*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | -0.2019*** | -0.2084*** | -0.2037*** | 0.3209*** | 0.3354*** | 0.1934*** | -0.2396*** | -0.2570*** | -0.2997*** |
| % Young People | 0.0135*** | 0.0115*** | 0.0091*** | 0.0155*** | 0.0096*** | 0.0099*** | 0.0096*** | 0.0078*** | 0.0077*** |
| Ethnic Heterogeneity | -0.0003 | -0.0009*** | -0.0014*** | -0.0033*** | -0.0031*** | -0.0031*** | -0.0010*** | -0.0018*** | -0.0013*** |
| % Low-income | 0.0075*** | 0.0071*** | 0.0052*** | 0.0235*** | 0.0232*** | 0.0274*** | 0.0239*** | 0.0225*** | 0.0210*** |
| Intercept | 0.9146*** | -9.3303*** | -9.5816*** | -6.1246*** | -16.8508*** | -15.1728*** | -0.2552 | -9.8157*** | -9.1444*** |

$*p < .05; **p < .01; ***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. These models also include an indicator for blocks that had zero population during a time interval. The 'yearly' models also include city fixed effects. These effects are not included in the table for parsimony. The table is unstandardized coefficients.*

## 5.4 Discussion

Criminologists, sociologists, and policymakers have long sought to better understand why some neighborhoods have more crime than others. This project was a first step to examining the spatial footprints of residents and the consequences of these spatial temporal movement patterns for crime rates. Using data from 13 cities across the US, I find that spatial footprints help to crystalize distinctions and similarities between routine activities theory and social disorganization theory. This project is strengthened by having a substantial amount of statistical and explanatory power along with local and federal data from 13 cities that vary drastically in geographic scope (across the entire United States) and population.

The results provide support for understanding the spatial and temporal implications of routine activities theory and social disorganization theory. Some of the effects from the models suggest more *enduring* spatial temporal patterns as might be suggested by social disorganization theory, while other effects were more *situational* to suggest a process more akin to routine activities theory. For example, many of the land use measures, housing, and low-income/poverty measures seemed to consistently matter regardless of the temporal specification (yearly, nightly, day and night) and spatial specification (both the focal block and nearby area). Whereas the enduring effects from social disorganization theory imply a broader spatial scale, other situational factors indicate a smaller spatial scale and are suggestive of a routine activities process. Young people, schools, and office land use effects often flipped signs over the day to indicate that the spatial footprint of residents at their different activities over the day helps to situate the opportunity from routine activities, particularly guardianship. Moreover, the opportunity for crime as suggested by routine activities theory is likely at a small situational scale given that many crimes require face-to-face contact.

Restaurants and grocery stores also showed interesting spatial effects in that in the focal neighborhoods these places are associated with more crime, suggestive of a opportunity effect, while living nearby these places, was suggestive of a protective enduring effect. This pattern suggests that the benefits of social ties might carry over to the nearby area. Living nearby a restaurant allows for more potential for social ties to be strengthened and possibly formed. The effects of social ties are arguably carried with people over time and space, particularly as they travel about their spatial footprints.

The effects of the different land use spaces and population variables over the day, week, and season are suggestive of different spatial footprints for different crime patterns. One consistent finding is that more people are always associated with more crime. This pattern is suggests the presence of the population over the day will provide evidence of whether different spaces of the city are expected to have more or less crime. More population is arguably indicative of a routine activities process due to more suitable targets or offenders, given that more population implicitly suggests more guardians. The types of crime that are likely to occur depends on the types of spaces being used (or not used) during a particular time of day and the processes for different crimes. For example, robberies are more likely to occur between a victim and offender who are strangers at night. This spatial and temporal insight offers clues to the overall crime generation process for different areas of the city, such as in retail spaces during the evening hours where there are more likely to be strangers. We also saw that larcenies and assaults had a particular pattern for school areas. Similarly, we see a micro opportunity effect for ethnic/racial similarity being associated with more homicides, and this seems reasonable given homicides are more likely to occur between people that are familiar with each other. These patterns suggest for future research to more explicitly consider the processes associated with different types of crime.

When examining robberies and many of the crimes for that matter, the effects for many of the measures, particularly land use measures, flipped signs or changed statistical significance when examining the three different models. This pattern of results suggests that the time of day, week, and season help to unpack the process of crime by situating the movements of potential guardians. For example, where as schools where expected to increase many of the different crime types in the yearly models, they actually have a protective effect for crimes when unpacking this effect to examine the people in these spaces over the day, which seems reasonable given that young people are expected to commit the most crime. Yet, for some crimes such as assaults and larcenies, these effects did not change and this might be due to the fact that these crimes are more likely to occur on or near school grounds. On the other hand, the effects from low-income and poverty were consistent regardless of the time of day. Future research might extend this pattern further by examining inequality over different hours of the day. For example, it is unclear when capturing the reference group for inequality whether people are referring to others in their local neighborhood or perhaps with another neighborhood, such as a work location.

While due in part to data limitations, researchers often only focus on people's homes (i.e., nighttime locations) and effectively ignore their temporary presence in other neighborhoods for various activities [125, 229, 230]. This raises the question: Is the home the best place to measure to understand crime patterns? While most people spend the majority of their time within and nearby their home, it is not clear whether this should be the best place to measure to capture crime and the extent of social control within the area. When examining the models from this paper, the results from the nighttime/home location models were often similar to the models that incorporate information with people in other spaces. The 'home' approach seems reasonable for some types of crimes such as burglary, but other crimes that are expected to be between strangers (i.e., robbery) and crimes against property (i.e., larceny) are less likely to be understood by the characteristics of the home locations. As suggested by the protective effect of office spaces, one possibility is that different locations may have their own forms of social control, including work colleagues or school teachers having a sense of community or collective efficacy. Future research might extend this finding by looking at the networks of movement patterns of people across the day with GPS or cell phone data.

Although little work discusses how neighborhoods are interdependent units [191], residents' spatial footprints link the focal neighborhood with the nearby neighborhood activity space. With residents traveling between different neighborhoods, the city and its neighborhoods become explicitly and theoretically interdependent. My approach to understanding residents' spatial footprints begins to problematize the approach in the neighborhoods literature where people are neatly bracketed into individual neighborhoods, which is often employed for studies using multilevel models. By embracing a model that allows for movement and interdependency between areas, it suggests forms of social control that are more situational and not necessarily related to the collective value and understandings of the residents. In other words, to the extent that neighborhoods are explicitly and theoretically interdependent, interlinking, and have permeable boundaries suggests an approach where neighborhoods have varying degrees of social control over time and space. At a minimum, it suggests that we need to measure areas outside of the focal neighborhood. Future research might extend these findings by explicitly modeling population commuting flows as a network of neighborhoods to gauge the popularity, expansiveness, and flow between different areas of the city.

This study has some limitations. First, while theoretically motivated around different activity patterns, there may be other possibilities for slicing up time into time interval categories (e.g. 3pm-5pm Monday- Friday). For example, other time interval categories should be assessed with empirical strategies or by adding other time interval categories, such as a time interval for lunch time or early evening hours during the week where work colleagues have more potential for interaction [60]. Nonetheless, the approach used to unpack time of day, day of week, and seasonality patterns from this study is a potentially useful for numerous social phenomena. Second, the strategy used here suggests people travel instantly between different activities. Future research might improve the current project by more appropriately incorporating traffic and other locations between the journey between two activities (e.g., the location of school children after school) [130]. Third, I have only focused on work and school locations, which likely captures much movement during the day, but I do not capture any movement during the evening hours. While I do capture the surrounding area using a 2.5 mile distance decay, as noted earlier, this might not be a reasonable spatial catchment area. Different covariates might also have unique spatial footprints, which suggests spatial buffers of varying sizes. For example, the catchment areas and distance decay for bars could be altered by the number of employees, economic resources, or ideally sales dates and times from different businesses. Moreover, the spatial catchment area could also be altered by the demographic characteristics of people expected to use bars, such as young people.

This chapter could be improved by developing better strategies for capturing the processes suggested by social disorganization theory and routine activities theory. For example, this study measures young people with the number of people in school and employed young people, but research has suggested that it is likely more appropriate to capture "unattached" young people [143]. Although it is unclear how to capture "unattached" youth (e.g., no prosocial peers?), future research might assess this possibility by examining spatial footprint patterns of delinquents. This might be accomplished with the land use data (e.g., recreational areas).

The findings and techniques from this study might be employed by police. Police departments increasingly use data mapping techniques and employ proactive problem oriented and predictive policing strategies to target high crime areas, rather than simply reacting to crime. Although these mapping techniques are frequently used by many police departments (e.g., in Los Angeles and Chicago), there are still fundamental challenges to this strategy: How large of an area should the police target (i.e., how big is a crime hot spot? A block? two blocks? A half-mile?)? Building on the work of Short et al. (2010) [206, 207] and Kennedy (2011) [107], future research might use the spatial footprint of residents to theoretically and empirically identify the size of hot spots, and where and when the areas nearby neighborhoods matter for crime control.

# Chapter 6

# Dissertation Conclusion

Criminology and many other fields suggest a variety of individual and group *motivations* - lack of mutual trust, norms, strains and expectation, inequality, lack of resources, social influence, social support, lack of control, and biological hard-wiring - as primary drivers of social phenomena, particularly crime. The explanation for more crime is generally given as the result of some group, area, or individual having more or less motivation or a change in motivation over long periods of time. While all of these motivations might be at work, in most instances different motivations are almost always assumed to be universally reasonable in space and time. It is often unclear where different motivations come from, how they are transmitted, and when they are active. While not only suggesting different policy implications, these motivations and mechanisms suggest differences in everyday life and spatial temporal *processes*. Using the spatial footprint, we can unpack and position these motivations and theories by putting them into action in everyday life. The spatial footprint is one approach for adding process to our theories by situating the opportunity, motivation, and actors in space, time, and interdependence.

As suggested earlier in this dissertation, an individual's participation in a variety of social institutions (i.e., the family, work, religion, school, peers) shapes much of daily life. Individuals' spatial footprint patterns arguably form the probability of two or more people being in a relationship, basis of attitudes, knowledge, perceptions, identity, and experiences. The spatial distribution of when different institutions are occupied suggests variability in the availability of opportunities for success, crime, and numerous other social phenomena. The theoretical mechanisms of interest from various theories do not simply exist but interact and change in space and time. The dosage, exposure, and consequences of various social institutions might be fundamentally dependent on spatial footprint patterns.

My dissertation was guided by the fact that people move around and are not isolated into only their nighttime home locations. It strives to approach social science phenomena with an explicit focus on space, time, and interdependence between people. Drawing from a variety of literatures, the challenges identified in the second chapter suggest that spatial footprints need to be considered in tandem with neighborhood processes. While most work only focuses on individual spatial footprint patterns, my dissertation suggests that the *population* of spatial footprint patterns have consequences for measurement of neighborhoods, the area nearby neighborhoods, availability of social control, and crime.

Distance was a particularly strong determinate of spatial footprint patterns in the third chapter. The plethora of individual and neighborhood (i.e., social) characteristics had much less of an effect. While most social phenomena are explained with fairly complicated explanations, this distance finding is particularly striking because of its simplicity. The fact that distance was a strong determinate of spatial footprints suggests that distance might explain many of the differences in motivations mentioned earlier (e.g., social influence is a result of physical distance between peers). The ability of a motivation process to become activated is likely dependent upon the space and time between people. The spatial footprint approach recognizes that not all motivations are equally accessible and active at all times and in all spaces. At a minimum, it appears that considerable traction can be made for understanding social phenomena by incorporating physical distance.

As another set of spatial characteristics, land uses were shown to be important for determining spatial footprints, collective efficacy, and crime patterns. While unclear when people were exactly occupying the various land uses, different types of spatial footprint activities were often linked explicitly to different land uses. Land uses might represent the potential for various social phenomena and spatial footprints, including when they are occupied and the activities within their spaces (e.g., industrial areas during the day). On a daily time scale, the land uses of the city and their *uneven* distribution situate where and when different spaces of the city are densely populated, the availability of opportunities for crime, and represent the baseline background template for social processes. Future research might extend these land use findings by adding a temporal component.

Given that we almost never observe the social process of interest (i.e., crime) in action, these spatial findings suggest that the spaces and times where crime takes place may give us considerable leverage for understanding social processes. Arguably the spatial temporal characteristics of a neighborhood represent the potential for social processes as much as demographic data (e.g., Census data) that only offers a rough proxy for social processes. This suggests that space and time are as important as demographic characteristics for understanding social processes. Nonetheless, most quantitative work in criminology and other fields often only employs demographic characteristics in their studies to represent social processes. My findings imply a need for studies to move beyond just demographic characteristics when studying individuals or neighborhoods and more explicitly incorporate space and time so that they do not misattribute social factors for spatial temporal factors (or vice versa). Space and time also have the added benefit of being easier to measure (e.g., retail area of a neighborhood vs. the social disorganization of a neighborhood).

In the fourth chapter, spatial footprint patterns and land uses had a significant effect on individual's perceptions of collective efficacy. The distance to different activities that were not necessarily directly linked to social ties or civic engagement had an impact on how people perceived their neighborhood. Through spatial footprint patterns, residents may form their expectations and awareness for different issues in and outside of the neighborhood. Nonetheless, residents' expectations for action in the neighborhood may not actually align with their behavior. As suggested in the 2nd chapter, the crucial link between spatial footprints and crime is *availability* of residents for social action, not necessarily just their expectations. Future research may want to examine more explicitly how often people are available, aware, willing, and capable for social control.

When looking at the results from chapter 5, the change in population for different areas was often substantial, and these patterns suggest changes in when different areas are at risk for crime and other social phenomena. My dissertation only focused on students and employees, and future research might extend these findings by incorporating the activity patterns of residents during the day and nighttime. The crime results suggested that some neighborhood factors (e.g., poverty) were *enduring* over the day as might be suggested by social disorganization theory. The spaces where social ties are arguably maintained, formed, and activated indicated a broader spatial scale as the benefits of ties were transmitted over to the nearby area. Spatial footprint patterns suggest distinctions for future work on how ties are maintained, formed, activated, and transmitted over space and time (e.g., ties forming vs. ties existing). At the same time, other factors (e.g., schools, offices, young people) were *situational* and changed considerably when incorporating spatial footprints over the day to suggest a process more akin to routine activities theory. The spatial footprint of residents over the day helped to situate the opportunity from routine activities, particularly guardianship, at a smaller situational spatial scale. When examining the models for cities and for times of day in the *Appendices*, there are evident differences among the cities and times of day. Taken as a whole, these findings suggest broader patterns of spatial footprints that are not isolated to one city, time point, or crime type.

A next step in spatial footprint research is to more explicitly theorize city level spatial temporal distinctions in crime patterns. We have little theoretical guidance in this area since neighborhood theories are usually not city specific or temporally specific. Less clear is why some cities might be different in their spatial footprint patterns, or why spatial footprint patterns have changed over the long-term (i.e., the crime drop). Drawing from the 2nd chapter, we might expect that different spatial layouts of cities (e.g. one urban core?), the states, and the regions in which they are embedded may offer some clues to understanding these broad trends. The population changes, seasonality, tourist population, and transportation infrastructure may offer clues, as well. Future research might examine the spatial footprint in relation to segregation in cities and/or the “crime drop”. One pattern of footprints might focus on deindustrialization of cities and the boom of the suburbs. Another process might suggest that changes in the spatial footprint of drug markets from outdoors to indoors might be indicative of the crime drop.

Similar to many other criminology studies, my dissertation focused on broad categories of crime. While more precise than a general ‘violent’ or ’property’ crime approach, the six crime types employed in this dissertation - homicide, robbery, assault, larceny, burglary, and motor vehicle theft - can be unpacked further with the spatial footprint. For example, robberies occur in a variety of different spaces (e.g. banks vs. the street), but this dissertation and most criminological research essentially treat all of these crimes as being equivalent by including them all in one robbery variable. This implies that the same social, temporal, and spatial characteristics that predict a bank robbery are the same for those that predict whether someone is robbed on the street. While some research has looked at this issue for homicides [117], there is little empirical work on other crime types (for a discussion of this issue for burglaries see [45, 119]). Using the spatial footprint, future research might examine these different crime patterns to specify how the availability of opportunity, space, and time situate different crime events.

In closing, the spatial footprint and the changing population patterns over the day, week, and season are fundamental to understanding crime in neighborhoods. The spatial footprint approach suggests a further need to better understand different crime processes at different spatial temporal scales. Somewhat akin to a public health approach, the risk of different individuals and neighborhoods are not equally situated in space and time. Using the measure of the daytime population from chapter 5, risk and exposure measures of different parts of cities might be used in hot spot and predictive policing. This is all to suggest that geography, time of day, and the spatial footprint are essential dimensions to understanding different crime processes. While this dissertation mostly focused on the consequences for crime patterns in cities, the spatial footprint approach can be used for other processes, including transportation, traffic, disease transmission, police resources and other public services, employment, population at risk during the day, environmental concerns, and public health amongst others.

# Appendices

# Appendix A: Crime and Land Use Data

### Crime Data

The crime data were collected from city police departments. Given these data are from police departments, they likely have the same limitations of all official data, including not all crimes being recorded or reported [138, 154]. Nonetheless, I have no reason to suspect that these data are any less valid than other official crime data sources. Importantly, research has shown that the structural characteristics of neighborhoods are not systematically related to reporting practices [8]. My six outcomes are Uniform Crime Report (UCR) Part 1 crimes: homicide, aggravated assault, robbery, burglary, larceny, and motor vehicle theft. A summary of each city's crime data and land use data are in Table .1.

For the majority of cities, I used a GIS to geocode the crime incidents to an exact latitude and longitude location. As a first attempt at geocoding the data, I used ESRI's 2010 Streetmap data. For some cities, this national address locator did not work well, and as result, I resorted to creating my own address locator with Tigerline roads, which is an approach used in ESRI's textbooks. The overall match rate was 94.2%. I used a 25 foot offset from the street, 70 spelling threshold, 10 match candidate, and 25 to be considered a match. While there is no gold standard for these thresholds, these values seemed to adequately cover the data and minimize error. For 5 cities, I was only able to obtain data obfuscated to the 100 block. To obtain an exact latitude and longitude coordinate for these 100 block area, I generated a random uniform number within the 100 block range, and this unique number was added to each address' street number before geocoding.

After geocoding the data, I used the resulting geographic coordinates to aggregate the data into blocks. To minimize instability in crime data over years, I use a 3 years of crime data from around 2010. Importantly, the crime data contain information on the date and time of day when the incident occurred.

For some cities, crime needed to be coded into crime categories. I did this by taking all unique crime types of the dataset and coding them into categories using the UCR guidelines. To assess coding issues in the crime data, I graphed each cities crime data by crime type, year, month, and by hour of the day (not shown). I also looked at mean changes over time. When an issue occurred, which was rare, I checked this city with the UCR's data to validate if the issue was a real coding issue or a substantial change. Finally, some cities did not make distinctions for some crime types (e.g. simple assault vs. aggravated assault).

**Land Use Data**

Land use data were obtained mostly from county planning departments (see Table .1) around 2010. All of the land use data are coded into parcels in the following categories: commercial/retail, industrial/manufacturing, white collar/office space, residential, schools, and other (e.g., parking, parks, agriculture, etc.). The classification system is in Table .2. The data was initially in parcels, and it was apportioned to Census blocks by area and aggregated to Census blocks (for a similar approach see [16]). For each category, a measure was created of the percent of the block area that is some land use type. Importantly, these land use data contain information for at least the entire county that a city is situated. Thus, when creating the land use spatial lags, they are not biased to areas just within the city.

Table .1: Land Use and Crime Data

| City | State | Total Blocks | Land Use Source | Land Use Year | Crime Years | Crime Geocoding Type | Crime Geocoding Score | Crime 100 Block | Crimes Not Available |
|---|---|---|---|---|---|---|---|---|---|
| Atlanta | GA | 6652 | Regional GIS | 2010 | 2009-2011 | StreetMap | 90.08 | | Homicide |
| Chicago | IL | 46324 | Regional GIS | 2005 | 2009-2011 | Police | | | Agg. Assault (Used General Assault) |
| Cincinnati | OH | 4582 | CNTY Planning | 2010 | 2009-2011 | StreetMap | 96.06 | | Agg. Assault |
| Cleveland | OH | N/A | City data | 2005 | N/A | N/A | N/A | N/A | No Crime Data |
| Columbus | OH | 13244 | CNTY Planning | 2005 | 2005-2007 | Police | | | Motor Vehicle Theft |
| Fresno | CA | 6653 | CNTY Planning | 2010 | 2009-2011 | StreetMap | 92.59 | X | Agg. Assault (Used General Assault) |
| Glendale | AZ | 3429 | CNTY Planning | 2010 | 2009-2011 | StreetMap | 96.01 | | |
| Houston | TX | 43439 | CNTY Tax Assessor | 2010 | 2009-2011 | Tigerline | 95.86 | | |
| Los Angeles | CA | 30691 | SCAG | 2010 | 2009-2011 | Tigerline | 94.75 | | |
| Oakland | CA | 6319 | CNTY Planning | 2010 | 2009-2011 | StreetMap | 94.04 | X | |
| Sacramento | CA | 7632 | CNTY Planning | 2010 | 2009-2011 | Tigerline | 94.5 | X | |
| San Jose | CA | 8082 | CNTY Planning | 2010 | 2009-2011 | Tigerline | 93.8 | X | |
| Scottsdale | AZ | 4055 | CNTY Planning | 2010 | 2009-2011 | StreetMap | 96.02 | X | |
| Tucson | AZ | 7736 | CNTY Planning | 2006 | 2009-2011 | StreetMap | 92.66 | | |

*Note: CNTY = County. SCAG = Southern California Association of Governments. Total N = 188,838 Blocks. Crime data is always from City Police. Land use source is where the land use data originated. Crime geocoding type indicates whether the data was geocoded by the police, using local county Census tigerline roads, or ArcGIS' StreetMap. Geocoding Match score was the overall match score after geocoding. 100 block indicates cities were crime addresses were specific to the 100 block. I randomly placed these along the 100 block. The crime categories are homicide, robbery, aggravated assault, larceny, burglary, and motor vehicle theft, unless otherwise indicated. Land use data includes area outside of the city boundary.*

Table .2: Land Use Categorization

| Detailed Land Use Categories | Classified Category |
|---|---|
| amusement facilities | commercial/retail |
| animal board/breed | commercial/retail |
| auto repair | commercial/retail |
| automobile dealership | commercial/retail |
| banks | commercial/retail |
| car/truck wash | commercial/retail |
| hotel/motel | commercial/retail |
| race track | commercial/retail |
| restaurant | commercial/retail |
| retail | commercial/retail |
| service stations | commercial/retail |
| strip development | commercial/retail |
| supermarket | commercial/retail |
| auto salvage | industrial/manufacturing |
| communication facilities | industrial/manufacturing |
| heavy equipment/truck lease or sale | industrial/manufacturing |
| heavy industry | industrial/manufacturing |
| natural gas and petroleum facilities | industrial/manufacturing |
| open storage | industrial/manufacturing |
| transportation | industrial/manufacturing |
| utilities | industrial/manufacturing |
| wrecking yards | industrial/manufacturing |
| offices | white collar/office space |
| condos | residential |

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Table .2 – *Continued from previous page*

| Detailed Land Use Categories | Classified Category |
|---|---|
| assisted living unit | residential |
| apartments | residential |
| single family unit | residential |
| mobile homes | residential |
| residential | residential |
| schools | school |
| colleges and universities | school |
| parking | other |
| parks | other |
| roads | other |
| alleys | other |
| agriculture | other |
| airports | other |
| cemeteries | other |
| correctional facilities | other |
| federal public | other |
| funeral home | other |
| institutional | other |
| landfill | other |
| large stadium | other |
| local public | other |
| medical | other |
| mixed use | other |
| motion picture and television studio lots | other |

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Table .2 – *Continued from previous page*

| Detailed Land Use Categories | Classified Category |
|---|---|
| nurseries | other |
| recreation | other |
| religious facilities | other |
| research and development | other |
| travel trailer or rv park | other |
| railroad | other |
| golf courses | other |
| veterinarian office | other |
| vacant | other |

# Appendix B: Discrete Choice Models for Location of Work, Church, Store, and School: Target and Similarity Interactions

Table .3: Discrete Choice Models for Location of Work, Church, Store, and School: Target and Similarity Interactions

| | Work | Church | Grocery Store | Child's School |
|---|---|---|---|---|
| | Coef. | Coef. | Coef. | Coef. |
| | (SE) | (SE) | (SE) | (SE) |
| **Target Neighborhood** | | | | |
| Same-Neighborhood (0/1) | 2.32913*** | -0.64394*** | -0.48922*** | 0.51539*** |
| | (0.17563) | (0.19131) | (0.10025) | (0.13852) |
| Log Distance (Miles) | -1.25015*** | -2.93374*** | -4.09963*** | -3.65952*** |
| | (0.19595) | (0.08003) | (0.07453) | (0.08249) |
| Log Distance * Log Distance | -0.16101*** | | | |
| | (0.04685) | | | |
| Intersection Density | -0.26896* | -0.18246 | 0.35880*** | -0.26762* |
| | (0.11750) | (0.15008) | (0.07946) | (0.12055) |
| % Residential LU | -0.00463** | -0.00480* | -0.00017 | -0.00393** |
| | (0.00152) | (0.00197) | (0.00117) | (0.00146) |
| % Industrial LU | 0.02083*** | -0.01527*** | 0.00309 | -0.00403 |
| | (0.00199) | (0.00463) | (0.00271) | (0.00329) |
| % Office LU | 0.03212*** | -0.00609 | -0.02945** | -0.05364** |
| | (0.00532) | (0.01672) | (0.01066) | (0.01643) |
| % School LU | -0.00317 | 0.01505** | -0.00157 | 0.03452*** |
| | (0.00438) | (0.00503) | (0.00355) | (0.00363) |
| % Retail LU | 0.01624*** | 0.00357 | 0.05050*** | 0.00292 |
| | (0.00453) | (0.00654) | (0.00321) | (0.00605) |
| # of Grocery Stores | 0.03372** | 0.03056 | 0.05876*** | 0.00959 |
| | (0.01188) | (0.02131) | (0.01327) | (0.01985) |
| # of Churches | 0.04151*** | 0.10206*** | 0.00512 | 0.07133*** |
| | (0.00820) | (0.01014) | (0.00962) | (0.01098) |
| **Household Characteristics** | | | | |
| Household Income (per 10k) | -0.01066 | -0.00369 | -0.00987** | -0.01077 |
| | (0.00560) | (0.00577) | (0.00353) | (0.00590) |

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Table .3 – *Continued from previous page*

| | Work | Church | Grocery Store | Child's School |
|---|---|---|---|---|
| | Coef. | Coef. | Coef. | Coef. |
| | (SE) | (SE) | (SE) | (SE) |
| Residential Tenure | -0.00486 | -0.00180 | -0.00414* | 0.00452 |
| | (0.00301) | (0.00246) | (0.00166) | (0.00368) |
| Employed (0/1) | | -0.02987 | -0.05732* | 0.00038 |
| | | (0.04501) | (0.02884) | (0.04147) |
| Homeowner (0/1) | 0.13137** | 0.03541 | 0.12230*** | 0.10923* |
| | (0.04991) | (0.04345) | (0.03362) | (0.04801) |
| Own Car (0/1) | 0.04970 | -0.01507 | 0.04150 | 0.00478 |
| | (0.05479) | (0.05652) | (0.02870) | (0.04640) |
| Married (0/1) | 0.04790 | -0.01366 | 0.02962 | 0.07269 |
| | (0.04089) | (0.04257) | (0.02714) | (0.03846) |
| Kids (0/1) | 0.17218*** | -0.00600 | 0.02022 | |
| | (0.04620) | (0.05409) | (0.03085) | |
| Female (0/1) | -0.16578*** | -0.05781 | -0.04218 | -0.00646 |
| | (0.03789) | (0.04025) | (0.02551) | (0.04035) |
| Black (0/1) | 0.17879 | 0.01427 | 0.07519 | 0.13591 |
| | (0.09730) | (0.08749) | (0.05769) | (0.09026) |
| Latino (0/1) | 0.04312 | -0.00555 | 0.03147 | 0.13144 |
| | (0.06628) | (0.07060) | (0.04898) | (0.07563) |
| White (0/1) | 0.12235 | 0.04147 | 0.00372 | 0.05065 |
| | (0.07192) | (0.07417) | (0.05251) | (0.08987) |
| Age (Years) | -0.00288 | -0.00068 | 0.00011 | 0.00203 |
| | (0.00210) | (0.00171) | (0.00107) | (0.00182) |
| **Target Neighborhood** | | | | |
| Population Density - Target | -0.00005*** | -0.00006*** | -0.00004*** | -0.00003*** |
| | (0.00001) | (0.00001) | (0.00001) | (0.00001) |
| Employee Density - Target | 0.09757*** | 0.02363 | 0.02774 | 0.01031 |
| | (0.01552) | (0.05998) | (0.02862) | (0.02873) |
| % Families with Children - Target | -0.01509** | 0.00880 | 0.02244*** | 0.01933*** |
| | (0.00541) | (0.00681) | (0.00442) | (0.00523) |
| % Black - Target | -0.00445 | -0.03169*** | -0.03959*** | -0.03312*** |
| | (0.00482) | (0.00698) | (0.00415) | (0.00507) |
| % Latino - Target | 0.00144 | -0.00785 | -0.03049*** | -0.01818*** |
| | (0.00289) | (0.00413) | (0.00258) | (0.00351) |
| % Asian - Target | -0.00696 | -0.00367 | -0.01067*** | -0.01203** |
| | (0.00441) | (0.00528) | (0.00303) | (0.00416) |
| % Other Race - Target | 0.06828*** | 0.05493 | -0.02039 | -0.01254 |

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Table .3 – *Continued from previous page*

| | Work | Church | Grocery Store | Child's School |
|---|---|---|---|---|
| | Coef. | Coef. | Coef. | Coef. |
| | (SE) | (SE) | (SE) | (SE) |
| | (0.01948) | (0.03222) | (0.02022) | (0.02928) |
| Median Income - Target | 0.06522 | -0.06827 | -0.28382*** | -0.07369 |
| | (0.04553) | (0.06308) | (0.04424) | (0.05705) |
| % Homeowner - Target | -0.00705* | 0.00470 | 0.01438*** | 0.01974*** |
| | (0.00307) | (0.00474) | (0.00281) | (0.00384) |
| % Vacant - Target | 0.01374 | 0.01116 | -0.01064 | 0.01442 |
| | (0.01088) | (0.02042) | (0.01024) | (0.01644) |
| **Neighborhood Similarity to Home** | | | | |
| Population Density - Similarity | 0.00001** | 0.00001 | 0.00005*** | -0.00000 |
| | (0.00000) | (0.00001) | (0.00001) | (0.00001) |
| Employee Density - Similarity | 0.03833** | 0.03856 | -0.02359 | 0.00260 |
| | (0.01466) | (0.02634) | (0.01299) | (0.01329) |
| % Families with Children - Similarity | 0.00704 | 0.04488* | -0.04391*** | 0.02884** |
| | (0.00813) | (0.01789) | (0.00785) | (0.01099) |
| % Black - Similarity | 0.00979* | 0.01628* | 0.02257*** | 0.02771* |
| | (0.00453) | (0.00788) | (0.00661) | (0.01090) |
| % Latino - Similarity | 0.00205 | 0.01096* | 0.01034** | 0.00506 |
| | (0.00274) | (0.00480) | (0.00357) | (0.00390) |
| % Asian - Similarity | 0.00554 | 0.00060 | 0.02061*** | 0.00659 |
| | (0.00421) | (0.00550) | (0.00569) | (0.00651) |
| % Other Race - Similarity | 0.06872** | 0.04659 | -0.03303 | -0.02459 |
| | (0.02101) | (0.03240) | (0.02877) | (0.03613) |
| Median Income - Similarity | -0.06286 | 0.01734 | 0.02535 | -0.03105 |
| | (0.03743) | (0.05671) | (0.05642) | (0.06965) |
| % Homeowner - Similarity | -0.00530 | -0.02470*** | -0.01875*** | -0.01923** |
| | (0.00327) | (0.00541) | (0.00413) | (0.00585) |
| % Vacant - Similarity | 0.03269** | 0.05661* | -0.01324 | -0.00719 |
| | (0.01093) | (0.02331) | (0.01023) | (0.01631) |
| **Target * Similarity Interactions** | | | | |
| Population Density - Interaction | -0.00000* | -0.00000* | -0.00000*** | 0.00000 |
| | (0.00000) | (0.00000) | (0.00000) | (0.00000) |
| Employee Density - Interaction | 0.00048* | 0.00542 | 0.01359** | 0.00024 |
| | (0.00021) | (0.00367) | (0.00442) | (0.00049) |
| % Families with Children - Interaction | -0.00009 | -0.00057* | 0.00096*** | -0.00052** |
| | (0.00016) | (0.00029) | (0.00015) | (0.00019) |
| % Black - Interaction | -0.00007 | -0.00050*** | -0.00041*** | -0.00041* |

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Table .3 – *Continued from previous page*

| | Work | Church | Grocery Store | Child's School |
|---|---|---|---|---|
| | Coef. | Coef. | Coef. | Coef. |
| | (SE) | (SE) | (SE) | (SE) |
| | (0.00010) | (0.00012) | (0.00010) | (0.00018) |
| % Latino - Interaction | 0.00002 | -0.00009 | -0.00012 | 0.00005 |
| | (0.00005) | (0.00009) | (0.00008) | (0.00010) |
| % Asian - Interaction | -0.00012 | 0.00016 | -0.00016 | 0.00003 |
| | (0.00011) | (0.00017) | (0.00010) | (0.00015) |
| % Other Race - Interaction | -0.00018 | 0.00152 | 0.01553** | 0.00868 |
| | (0.00070) | (0.00134) | (0.00540) | (0.00627) |
| Median Income - Interaction | 0.00497 | -0.00647 | -0.00694 | -0.00020 |
| | (0.00526) | (0.00650) | (0.00726) | (0.00659) |
| % Homeowner - Interaction | -0.00000 | 0.00047*** | 0.00025*** | 0.00028*** |
| | (0.00006) | (0.00011) | (0.00007) | (0.00008) |
| % Vacant - Interaction | -0.00040* | -0.00014 | -0.00053*** | 0.00405* |
| | (0.00017) | (0.00138) | (0.00013) | (0.00194) |
| Intercept | -2.52418*** | -0.16197 | 1.30302*** | -0.89754 |
| | (0.46614) | (0.62795) | (0.37295) | (0.53344) |
| Pseudo R-Square | 0.25808 | 0.36556 | 0.50146 | 0.48440 |

*Note:* SE = Standard error, LU = Land Use. * = $p < .05$; ** = $p < .01$; *** = $p < .001$

# Appendix C: Discrete Choice Models for Location of Work, Church, Store, and School: Distance and Household Characteristics Interactions

Table .4: Discrete Choice Models for Location of Work, Church, Store, and School: Distance and Household Characteristics Interactions

| | Work | Church | Grocery Store | Child's School |
|---|---|---|---|---|
| | Coef. | Coef. | Coef. | Coef. |
| | (SE) | (SE) | (SE) | (SE) |
| **Target Neighborhood** | | | | |
| Same-Neighborhood (0/1) | 2.43998*** | -0.61141** | -0.39666*** | 0.47528*** |
| | (0.17721) | (0.19230) | (0.09886) | (0.13475) |
| Log Distance (Miles) | -1.18094*** | -2.30100*** | -4.23938*** | -5.14911*** |
| | (0.28798) | (0.42062) | (0.33687) | (0.28108) |
| Log Distance * Log Distance | -0.20727*** | | | |
| | (0.04747) | | | |
| Intersection Density | -0.25362* | -0.15562 | 0.32323*** | -0.24086* |
| | (0.11720) | (0.14715) | (0.07997) | (0.11842) |
| % Residential LU | -0.00422** | -0.00431* | 0.00101 | -0.00345* |
| | (0.00148) | (0.00196) | (0.00117) | (0.00144) |
| % Industrial LU | 0.02155*** | -0.01240** | 0.00693** | -0.00480 |
| | (0.00197) | (0.00436) | (0.00247) | (0.00320) |
| % Office LU | 0.03671*** | 0.00264 | -0.02167* | -0.05035*** |
| | (0.00488) | (0.01509) | (0.00914) | (0.01454) |
| % School LU | -0.00288 | 0.01454** | 0.00180 | 0.03076*** |
| | (0.00405) | (0.00481) | (0.00383) | (0.00338) |
| % Retail LU | 0.01768*** | 0.00890 | 0.05387*** | 0.00278 |
| | (0.00443) | (0.00619) | (0.00288) | (0.00583) |
| # of Grocery Stores | 0.03678** | 0.01714 | 0.06183*** | 0.01255 |
| | (0.01145) | (0.02100) | (0.01249) | (0.02018) |
| # of Churches | 0.04270*** | 0.10532*** | 0.00172 | 0.06891*** |
| | (0.00814) | (0.01005) | (0.00974) | (0.01113) |
| Population Density - Target | -0.00004*** | -0.00006*** | -0.00003*** | -0.00004*** |

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Table .4 – *Continued from previous page*

| | Work | Church | Grocery Store | Child's School |
|---|---|---|---|---|
| | Coef. | Coef. | Coef. | Coef. |
| | (SE) | (SE) | (SE) | (SE) |
| | (0.00001) | (0.00001) | (0.00000) | (0.00001) |
| Employee Density - Target | 0.07206*** | -0.03141 | -0.05924*** | -0.00530 |
| | (0.01402) | (0.04305) | (0.01684) | (0.02190) |
| % Families with Children - Target | -0.01410*** | 0.01022 | 0.00360 | 0.02247*** |
| | (0.00423) | (0.00559) | (0.00345) | (0.00432) |
| % Black - Target | -0.00354 | -0.01073 | -0.03226*** | -0.02510*** |
| | (0.00400) | (0.00598) | (0.00412) | (0.00473) |
| % Latino - Target | -0.00006 | -0.00461 | -0.02892*** | -0.01841*** |
| | (0.00254) | (0.00351) | (0.00247) | (0.00302) |
| % Asian - Target | -0.00392 | -0.00595 | -0.00846** | -0.01258*** |
| | (0.00363) | (0.00470) | (0.00294) | (0.00368) |
| % Other Race - Target | 0.07023*** | 0.04770 | -0.06742*** | -0.02198 |
| | (0.01718) | (0.02810) | (0.01441) | (0.02281) |
| Median Income - Target | 0.04256 | -0.02548 | -0.27095*** | -0.01664 |
| | (0.03112) | (0.05127) | (0.04189) | (0.04865) |
| % Homeowner - Target | -0.00639** | -0.00835* | 0.01000*** | 0.01185*** |
| | (0.00231) | (0.00396) | (0.00233) | (0.00323) |
| % Vacant - Target | 0.01763 | 0.00262 | -0.00528 | -0.01649 |
| | (0.01025) | (0.01620) | (0.00913) | (0.01198) |
| **Neighborhood Similarity to Home** | | | | |
| Population Density - Similarity | 0.00001 | -0.00000 | 0.00002*** | -0.00000 |
| | (0.00000) | (0.00001) | (0.00000) | (0.00001) |
| Employee Density - Similarity | 0.03965** | 0.05747 | 0.01594 | 0.00536 |
| | (0.01400) | (0.02949) | (0.00906) | (0.01330) |
| % Families with Children - Similarity | 0.00320 | 0.01657* | 0.00535 | 0.00164 |
| | (0.00394) | (0.00724) | (0.00498) | (0.00552) |
| % Black - Similarity | 0.00806 | 0.00899 | 0.00709 | 0.01058 |
| | (0.00417) | (0.00563) | (0.00446) | (0.00620) |
| % Latino - Similarity | 0.00225 | 0.00752* | 0.00539* | 0.00538 |
| | (0.00186) | (0.00329) | (0.00253) | (0.00300) |
| % Asian - Similarity | 0.00398 | 0.00066 | 0.01671*** | 0.00747 |
| | (0.00342) | (0.00524) | (0.00422) | (0.00510) |
| % Other Race - Similarity | 0.06184*** | 0.04550 | 0.02664 | 0.02241 |
| | (0.01726) | (0.02791) | (0.02024) | (0.02554) |
| Median Income - Similarity | -0.01268 | -0.00718 | 0.02177 | 0.06122 |
| | (0.02508) | (0.04500) | (0.03134) | (0.04728) |

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Table .4 – *Continued from previous page*

| | Work | Church | Grocery Store | Child's School |
|---|---|---|---|---|
| | Coef. | Coef. | Coef. | Coef. |
| | (SE) | (SE) | (SE) | (SE) |
| % Homeowner - Similarity | -0.00623** | -0.00725 | -0.00678** | -0.00774* |
| | (0.00203) | (0.00400) | (0.00244) | (0.00349) |
| % Vacant - Similarity | 0.01864 | 0.05903** | -0.02846** | 0.01736 |
| | (0.01042) | (0.01808) | (0.00946) | (0.01357) |
| **Household Characteristics and Interactions** | | | | |
| Household Income (per 10k) | -0.02296 | 0.00504 | -0.00444 | -0.02624 |
| | (0.01712) | (0.01579) | (0.00996) | (0.01518) |
| Household Income * Distance | 0.00726 | 0.00127 | -0.00617 | 0.01713 |
| | (0.00907) | (0.01361) | (0.01105) | (0.01305) |
| Residential Tenure | 0.00810 | -0.00232 | 0.00273 | -0.01205 |
| | (0.01031) | (0.00903) | (0.00524) | (0.00951) |
| Residential Tenure * Distance | -0.00722 | -0.00199 | -0.00858 | 0.01732 |
| | (0.00545) | (0.00806) | (0.00635) | (0.00938) |
| Employed (0/1) | | -0.19821 | 0.05015 | -0.29857* |
| | | (0.16953) | (0.09133) | (0.12322) |
| Employed * Distance | | 0.12577 | -0.15052 | 0.34005* |
| | | (0.15570) | (0.11817) | (0.14041) |
| Homeowner (0/1) | -0.24300 | 0.27882 | -0.25379* | -0.04494 |
| | (0.17113) | (0.16010) | (0.09874) | (0.13415) |
| Homeowner * Distance | 0.21949* | -0.12696 | 0.51503*** | 0.21659 |
| | (0.09101) | (0.13026) | (0.12049) | (0.14185) |
| Own Car (0/1) | -0.36426* | 0.23268 | -0.40756*** | 0.04044 |
| | (0.16586) | (0.17853) | (0.11106) | (0.14499) |
| Own Car * Distance | 0.27653** | -0.15185 | 0.66435*** | -0.02588 |
| | (0.10358) | (0.16444) | (0.15780) | (0.17571) |
| Married (0/1) | -0.01421 | 0.00838 | -0.17848* | 0.05876 |
| | (0.14208) | (0.14742) | (0.08911) | (0.12367) |
| Married *Distance | 0.03739 | -0.02676 | 0.27460* | 0.01112 |
| | (0.07980) | (0.13219) | (0.11192) | (0.13889) |
| Kids (0/1) | 0.19794 | 0.15058 | 0.12266 | |
| | (0.16416) | (0.18993) | (0.10295) | |
| Kids * Distance | -0.01618 | -0.12853 | -0.13266 | |
| | (0.09309) | (0.16531) | (0.13146) | |
| Female (0/1) | 0.02672 | -0.33746* | -0.13552 | -0.18197 |
| | (0.12754) | (0.15013) | (0.08339) | (0.11454) |
| Female * Distance | -0.11247 | 0.24381 | 0.12299 | 0.19370 |

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Table .4 – *Continued from previous page*

| | Work | Church | Grocery Store | Child's School |
|---|---|---|---|---|
| | Coef. | Coef. | Coef. | Coef. |
| | (SE) | (SE) | (SE) | (SE) |
| | (0.07093) | (0.13364) | (0.10441) | (0.12405) |
| Black (0/1) | -0.09581 | -1.12281*** | -0.05857 | -0.45658* |
| | (0.31989) | (0.32022) | (0.15879) | (0.22120) |
| Black *Distance | 0.14825 | 0.64882** | 0.12596 | 0.54571** |
| | (0.16657) | (0.22327) | (0.18258) | (0.20459) |
| Latino (0/1) | 0.10576 | 0.33535 | 0.37346** | 0.08039 |
| | (0.21344) | (0.26502) | (0.13628) | (0.07674) |
| Latino *Distance | -0.03116 | -0.37075 | -0.42152** | |
| | (0.11702) | (0.20132) | (0.16091) | |
| White (0/1) | 0.10510 | 0.40777 | 0.00018 | -0.62888*** |
| | (0.23420) | (0.27864) | (0.14028) | (0.18379) |
| White * Distance | 0.02853 | -0.26264 | 0.05760 | 0.67558*** |
| | (0.12961) | (0.20668) | (0.16139) | (0.16317) |
| Age (Years) | 0.00456 | 0.01411* | 0.00782* | -0.00975 |
| | (0.00647) | (0.00643) | (0.00376) | (0.00505) |
| Age * Distance | -0.00433 | -0.01032 | -0.00873 | 0.01479** |
| | (0.00369) | (0.00566) | (0.00506) | (0.00520) |
| Intercept | -2.65618*** | -1.12179 | 2.13390*** | 0.52104 |
| | (0.51498) | (0.72813) | (0.41541) | (0.51541) |
| Pseudo R-Square | 0.25906 | 0.36617 | 0.50152 | 0.48790 |

*Note:* SE = Standard error, LU = Land Use. Model with Latino * distance interaction did not converge for the school choice model. $* = p < .05$; $** = p < .01$; $*** = p < .001$

# Appendix D: Models for each Time of Day

See next page.

Table .5: Winter Assault

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00692*** | 0.00076 | -0.00038 | 0.00172 | 0.00439 | -0.00531* | -0.00491 |
| % Residential LU | -0.00517*** | -0.00724*** | -0.00809*** | -0.00773*** | -0.00550*** | -0.00706*** | -0.00634*** |
| % Retail LU | 0.00362* | 0.00229 | 0.00588*** | 0.00912*** | 0.00995*** | 0.00992*** | 0.01493*** |
| % Office LU | -0.00960** | -0.00624 | -0.00326 | 0.00276 | 0.00022 | -0.00897** | 0.00853* |
| % School LU | 0.00762*** | 0.01093*** | -0.00289 | 0.00598** | -0.00340 | 0.00004 | -0.00340 |
| # of bars | -0.01858 | 0.03118 | 0.17410* | 0.50947*** | -0.02529 | 0.52027*** | 0.99614*** |
| # of grocery stores | 0.27047*** | 0.26599*** | 0.26865*** | 0.23786*** | 0.26696*** | 0.31825*** | 0.14899 |
| # of restaurants | 0.07261** | 0.02481 | 0.12636*** | 0.10634*** | 0.16335*** | 0.11666*** | 0.10568** |
| **Housing** | | | | | | | |
| % Homeowners | -0.01024*** | -0.00824*** | -0.01027*** | -0.01147*** | -0.01014*** | -0.00951*** | -0.00794*** |
| % Vacant Units | 0.00937*** | 0.00904*** | 0.00983*** | 0.00873*** | 0.00993*** | 0.00907*** | 0.01350*** |
| **Time Varying** | | | | | | | |
| Logged Population | 0.50830*** | 0.50627*** | 0.61073*** | 0.57573*** | 0.61150*** | 0.60013*** | 0.60033*** |
| % Young People | 0.00170 | -0.00120 | -0.00565*** | -0.00492* | -0.00807*** | -0.00023 | -0.00101 |
| Ethnic Heterogeneity | 0.00103 | 0.00290* | -0.00022 | 0.00032 | -0.00093 | -0.00255* | -0.00302 |
| % Low-income | 0.00365*** | 0.00791*** | 0.00506*** | 0.00522*** | 0.00400** | 0.00261* | -0.00078 |

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Table .5 – *Continued from previous page*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.01678*** | 0.00736 | 0.00593 | 0.00541 | 0.00601 | 0.01542*** | -0.00281 |
| % Residential LU | 0.00525** | 0.00000 | 0.00479** | 0.01130*** | 0.00666** | 0.00722** | 0.00715* |
| % Retail LU | 0.01550** | -0.01005 | 0.00777 | 0.01535** | 0.01144* | -0.00590 | 0.02269*** |
| % Office LU | -0.09564*** | -0.06776** | -0.08174*** | -0.04695** | -0.11120*** | -0.02778 | -0.05381* |
| % School LU | 0.07719*** | 0.07346*** | 0.02023 | 0.00229 | -0.02758 | 0.03062* | -0.03279 |
| # of bars | 0.00160 | 0.00090 | 0.00274** | 0.00149 | 0.00356* | 0.00492*** | 0.00867*** |
| # of grocery stores | -0.00049 | -0.00178 | -0.00230*** | -0.00215** | -0.00126 | -0.00124 | -0.00143 |
| # of restaurants | -0.00044 | -0.00009 | -0.00061** | -0.00001 | -0.00035 | -0.00087** | -0.00081* |
| **Housing** | | | | | | | |
| % Homeowners | 0.00146 | 0.00269 | 0.01566*** | 0.01519*** | 0.01656*** | 0.01395*** | 0.02058*** |
| % Vacant Units | 0.05474*** | 0.02278* | 0.03827*** | 0.04968*** | 0.03282*** | 0.02468** | 0.04913*** |
| **Time Varying** | | | | | | | |
| Logged Population | 0.04620 | -0.03718 | 0.33596*** | -0.02609 | -0.06967 | 0.08680 | 0.10517 |
| % Young People | -0.03989*** | -0.01779 | 0.00414 | 0.01899** | 0.01721* | 0.00510 | 0.02703*** |
| Ethnic Heterogeneity | -0.00105 | 0.00099 | 0.00107 | -0.00074 | 0.00152 | 0.00053 | 0.00268 |
| % Low-income | 0.03464*** | 0.04030*** | 0.04327*** | 0.04146*** | 0.05249*** | 0.04766*** | 0.05041*** |
| Intercept | -13.70851*** | -12.28348*** | -18.38857*** | -15.58371*** | -14.60391*** | -15.70089*** | -17.99613*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: LU = Land Use. Table is unstandardized coefficients.*

Table .6: Spring Assault

| | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00308 | -0.00306 | -0.00514** | 0.00091 | -0.00232 | -0.00240 | 0.00103 |
| % Residential LU | -0.00575*** | -0.00567*** | -0.00675*** | -0.00839*** | -0.00811*** | -0.00704*** | -0.00741*** |
| % Retail LU | 0.00121 | 0.00141 | 0.00745*** | 0.00802*** | 0.00444* | 0.00705*** | 0.01318*** |
| % Office LU | -0.00430 | -0.00463 | -0.00528* | -0.00138 | -0.00322 | -0.00331 | 0.00224 |
| % School LU | 0.00773*** | 0.01485*** | 0.00298 | 0.00448* | -0.00216 | 0.00287 | 0.00052 |
| # of bars | 0.06223 | -0.00003 | 0.29181*** | 0.53409*** | 0.16063 | 0.34565*** | 1.04370*** |
| # of grocery stores | 0.27829*** | 0.25956*** | 0.24988*** | 0.20118*** | 0.25527*** | 0.31118*** | 0.13893 |
| # of restaurants | 0.08970*** | 0.10326*** | 0.08014*** | 0.12481*** | 0.10851*** | 0.15028*** | 0.13774*** |
| **Housing** | | | | | | | |
| % Homeowners | -0.01027*** | -0.00844*** | -0.00964*** | -0.00897*** | -0.00930*** | -0.00953*** | -0.00982*** |
| % Vacant Units | 0.00916*** | 0.01026*** | 0.01059*** | 0.01151*** | 0.00726*** | 0.01103*** | 0.01254*** |
| **Time Varying** | | | | | | | |
| Logged Population | 0.45799*** | 0.50411*** | 0.59719*** | 0.58103*** | 0.60836*** | 0.59628*** | 0.53495*** |
| % Young People | 0.00119 | -0.00100 | -0.00414** | 0.00016 | -0.00245 | -0.00313 | -0.00100 |
| Ethnic Heterogeneity | 0.00138 | 0.00028 | -0.00183* | -0.00005 | -0.00092 | -0.00177 | -0.00070 |
| % Low-income | 0.00347*** | 0.00586*** | 0.00425*** | 0.00534*** | 0.00386** | 0.00605*** | 0.00241 |

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Table .6 – *Continued from previous page*

| | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.01003* | 0.01591** | 0.01230*** | 0.01114** | 0.00828 | 0.00621 | 0.00459 |
| % Residential LU | 0.00130 | 0.00090 | 0.00852*** | 0.00996*** | 0.00387 | 0.00034 | 0.00467 |
| % Retail LU | 0.00681 | 0.00957 | 0.01547*** | 0.01532*** | 0.01492*** | 0.00265 | 0.01802** |
| % Office LU | -0.06484*** | -0.07606*** | -0.07000*** | -0.05874*** | -0.08130*** | -0.05055*** | -0.00712 |
| % School LU | 0.06047*** | 0.06593*** | 0.02458* | -0.02031 | -0.00025 | 0.01666 | -0.03463 |
| # of bars | -0.00014 | -0.00102 | 0.00164* | 0.00375*** | 0.00256* | 0.00475*** | 0.00674*** |
| # of grocery stores | -0.00023 | 0.00078 | -0.00158** | -0.00152* | -0.00107 | -0.00209** | -0.00151 |
| # of restaurants | -0.00064** | -0.00014 | -0.00014 | -0.00051* | -0.00052* | -0.00103*** | -0.00087** |
| **Housing** | | | | | | | |
| % Homeowners | -0.00487* | 0.01164*** | 0.01888*** | 0.01017*** | 0.02106*** | 0.01642*** | 0.02231*** |
| % Vacant Units | 0.04490*** | 0.04320*** | 0.03512*** | 0.03630*** | 0.05477*** | 0.04031*** | 0.03913*** |
| **Time Varying** | | | | | | | |
| Logged Population | 0.03124 | 0.03404 | -0.00509 | -0.06037 | 0.11338 | 0.34285*** | 0.25429 |
| % Young People | -0.03132*** | -0.00669 | 0.00803 | 0.01250* | 0.00354 | 0.00067 | 0.02146** |
| Ethnic Heterogeneity | -0.00278* | -0.00037 | 0.00171 | 0.00125 | 0.00095 | 0.00199 | 0.00043 |
| % Low-income | 0.03117*** | 0.02765*** | 0.05035*** | 0.04190*** | 0.04502*** | 0.04243*** | 0.04888*** |
| Intercept | -12.03044*** | -13.38445*** | -14.65590*** | -14.42866*** | -16.15026*** | -17.94498*** | -18.61904*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: LU = Land Use. Table is unstandardized coefficients.*

Table .7: Summer Assault

| | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|
| | 7am-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | |
| % Industrial LU | -0.00407** | -0.00047 | -0.00143 | 0.00205 | -0.00339 | 0.00173 |
| % Residential LU | -0.00472*** | -0.00680*** | -0.00755*** | -0.00606*** | -0.00783*** | -0.00502*** |
| % Retail LU | 0.00223 | 0.00756*** | 0.01050*** | 0.00491** | 0.00661*** | 0.01296*** |
| % Office LU | -0.00755*** | -0.00322 | 0.00061 | -0.00307 | -0.00257 | 0.00488 |
| % School LU | -0.00508*** | 0.00012 | -0.00135 | -0.00169 | -0.00123 | -0.00509 |
| # of bars | 0.00751 | 0.07558 | 0.38718*** | 0.28030** | 0.26605** | 0.57394*** |
| # of grocery stores | 0.26705*** | 0.26617*** | 0.20203*** | 0.28481*** | 0.13335** | |
| # of restaurants | 0.09148*** | 0.11815*** | 0.11027*** | 0.11644*** | 0.14373*** | 0.16871*** |
| **Housing** | | | | | | |
| % Homeowners | -0.01101*** | -0.00953*** | -0.01045*** | -0.01093*** | -0.00973*** | -0.01110*** |
| % Vacant Units | 0.00881*** | 0.00846*** | 0.00856*** | 0.00863*** | 0.01143*** | 0.00814*** |
| **Time Varying** | | | | | | |
| Logged Population | 0.47624*** | 0.61012*** | 0.57989*** | 0.57685*** | 0.62841*** | 0.55405*** |
| % Young People | 0.00115 | -0.00424*** | -0.00086 | -0.00334 | -0.00537** | 0.00065 |
| Ethnic Heterogeneity | 0.00032 | 0.00070 | 0.00059 | 0.00015 | -0.00299** | -0.00223 |
| % Low-income | 0.00326*** | 0.00442*** | 0.00657*** | 0.00720*** | 0.00365*** | 0.00171 |

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Table .7 – *Continued from previous page*

| | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|
| | 7am-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | |
| **Land Use and Business** | | | | | | |
| % Industrial LU | 0.01906*** | 0.00977** | 0.00163 | 0.00198 | 0.02135*** | 0.01213* |
| % Residential LU | 0.00282* | 0.00589*** | 0.01035*** | 0.00653** | 0.00910*** | 0.00346 |
| % Retail LU | 0.01494*** | 0.00975** | 0.01662*** | 0.01293** | 0.01240** | 0.00897 |
| % Office LU | -0.08974*** | -0.06294*** | -0.03208* | -0.06832*** | -0.04161** | -0.02369 |
| % School LU | 0.05458*** | 0.02591** | 0.00200 | 0.03128* | -0.00113 | -0.02408 |
| # of bars | 0.00103 | 0.00438*** | 0.00768*** | 0.00374** | 0.00477*** | 0.00708*** |
| # of grocery stores | 0.00005 | -0.00229*** | -0.00174** | -0.00204** | -0.00182** | 0.00092 |
| # of restaurants | -0.00060*** | -0.00088*** | -0.00097*** | -0.00049 | -0.00090*** | -0.00098*** |
| **Housing** | | | | | | |
| % Homeowners | 0.00287 | 0.01603*** | 0.01688*** | 0.01694*** | 0.01353*** | 0.02151*** |
| % Vacant Units | 0.06565*** | 0.02715*** | 0.04635*** | 0.04018*** | 0.02216** | 0.04617*** |
| **Time Varying** | | | | | | |
| Logged Population | 0.06122 | 0.13589 | -0.04669 | 0.01215 | 0.08300 | 0.28424* |
| % Young People | -0.02838*** | 0.00405 | 0.00608 | 0.00374 | 0.00715 | 0.00856 |
| Ethnic Heterogeneity | -0.00163 | 0.00104 | 0.00368** | 0.00110 | 0.00274* | 0.00335 |
| % Low-income | 0.02844*** | 0.05105*** | 0.04860*** | 0.04576*** | 0.04816*** | 0.04278*** |
| Intercept | -13.14669*** | -15.61068*** | -15.06304*** | -14.77633*** | -15.07218*** | -18.79525*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .8: Fall Assault

| | 21 | 22 | 23 | 24 | 25 | 26 | 27 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00581** | -0.00562* | 0.00009 | 0.00177 | -0.00054 | -0.00141 | 0.00155 |
| % Residential LU | -0.00481*** | -0.00652*** | -0.00772*** | -0.00687*** | -0.00744*** | -0.00769*** | -0.00765*** |
| % Retail LU | 0.00114 | 0.00394 | 0.00302* | 0.01012*** | 0.00540** | 0.00904*** | 0.00951*** |
| % Office LU | -0.00848** | -0.00710 | -0.00681** | 0.00060 | 0.00181 | -0.00141 | 0.00089 |
| % School LU | 0.00531*** | 0.01103*** | -0.00195 | 0.00534* | 0.00012 | -0.00370 | -0.00290 |
| # of bars | 0.11325 | 0.15432 | 0.27521*** | 0.56262*** | 0.21677* | 0.27567** | 0.60729*** |
| # of grocery stores | 0.17683*** | 0.33045*** | 0.22127*** | 0.23631*** | 0.29414*** | 0.25818*** | 0.23718** |
| # of restaurants | 0.13052*** | 0.06222 | 0.12622*** | 0.16860*** | 0.10043*** | 0.13364*** | 0.15656*** |
| **Housing** | | | | | | | |
| % Homeowners | -0.01139*** | -0.00853*** | -0.01000*** | -0.01205*** | -0.01000*** | -0.00977*** | -0.00905*** |
| % Vacant Units | 0.00540*** | 0.00920*** | 0.01118*** | 0.01004*** | 0.00733*** | 0.00836*** | 0.00903*** |
| **Time Varying** | | | | | | | |
| Logged Population | 0.48635*** | 0.50279*** | 0.61921*** | 0.51792*** | 0.56781*** | 0.58398*** | 0.51736*** |
| % Young People | 0.00057 | -0.00003 | -0.00246 | -0.00088 | -0.00139 | -0.00291 | 0.00159 |
| Ethnic Heterogeneity | 0.00109 | 0.00122 | -0.00018 | 0.00105 | 0.00172 | -0.00225* | -0.00127 |
| % Low-income | 0.00396*** | 0.00685*** | 0.00436*** | 0.00305** | 0.00153 | 0.00358** | 0.00413** |

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Table .8 – *Continued from previous page*

| | 21 | 22 | 23 | 24 | 25 | 26 | 27 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.01372*** | 0.00827 | 0.00529 | -0.00098 | 0.00238 | 0.01207** | 0.02000*** |
| % Residential LU | 0.00110 | -0.00040 | 0.00481** | 0.00972*** | 0.00731*** | 0.00781*** | 0.00517 |
| % Retail LU | 0.01070** | 0.01059 | 0.01106** | 0.00972* | 0.01427** | 0.01772*** | 0.01003 |
| % Office LU | -0.09315*** | -0.07659*** | -0.08751*** | -0.03248* | -0.07827*** | -0.03896** | 0.01105 |
| % School LU | 0.05175*** | 0.04341* | 0.01084 | 0.00986 | 0.01647 | 0.00514 | -0.01767 |
| # of bars | 0.00013 | 0.00106 | 0.00231** | 0.00554*** | 0.00370** | 0.00481*** | 0.00634*** |
| # of grocery stores | 0.00042 | -0.00165 | -0.00241*** | -0.00201** | -0.00017 | -0.00149* | -0.00303** |
| # of restaurants | -0.00067** | -0.00083* | -0.00041* | -0.00039 | -0.00085** | -0.00104*** | -0.00061 |
| **Housing** | | | | | | | |
| % Homeowners | 0.00398 | 0.00439 | 0.01728*** | 0.01391*** | 0.01009** | 0.01685*** | 0.01619*** |
| % Vacant Units | 0.06021*** | 0.04092*** | 0.02939*** | 0.03830*** | 0.03455*** | 0.03044*** | 0.01609 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.09651 | 0.17402 | 0.14722 | -0.10866 | -0.09003 | 0.17008 | 0.28107* |
| % Young People | -0.01640* | -0.02209* | 0.01446** | 0.00276 | 0.00229 | 0.01474* | 0.02103** |
| Ethnic Heterogeneity | -0.00180 | -0.00091 | 0.00055 | 0.00154 | -0.00165 | 0.00366* | 0.00250 |
| % Low-income | 0.02941*** | 0.02718*** | 0.04865*** | 0.04977*** | 0.04577*** | 0.04941*** | 0.04493*** |
| Intercept | -13.93590*** | -13.84554*** | -16.19906*** | -13.96314*** | -12.99648*** | -16.62042*** | -18.25922*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .9: Winter Robbery

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00815*** | -0.00193 | -0.00331* | -0.00061 | 0.00341 | -0.00312 | 0.00335 |
| % Residential LU | -0.00908*** | -0.00890*** | -0.01008*** | -0.01131*** | -0.01171*** | -0.00993*** | -0.01097*** |
| % Retail LU | 0.00981*** | 0.01212*** | 0.01429*** | 0.01134*** | 0.01407*** | 0.01392*** | 0.01030*** |
| % Office LU | -0.00466 | -0.00354 | -0.00045 | -0.00071 | 0.00293 | 0.00000 | -0.00431 |
| % School LU | -0.00863*** | 0.00760** | 0.00240 | 0.00102 | 0.00327 | -0.00125 | -0.00364 |
| # of bars | 0.16190 | 0.15770 | 0.16565* | 0.22255** | 0.14785 | 0.04920 | 0.13186 |
| # of grocery stores | 0.43141*** | 0.53162*** | 0.48381*** | 0.37181*** | 0.40553*** | 0.48982*** | 0.39733*** |
| # of restaurants | 0.16400*** | 0.06331* | 0.19049*** | 0.17499*** | 0.21824*** | 0.17145*** | 0.16676*** |
| **Housing** | | | | | | | |
| % Homeowners | -0.00556*** | -0.00437*** | -0.00746*** | -0.00848*** | -0.00728*** | -0.00901*** | -0.00676*** |
| % Vacant Units | 0.00861*** | 0.01102*** | 0.00945*** | 0.00931*** | 0.00877*** | 0.00883*** | 0.00892*** |
| **Time Varying** | | | | | | | |
| Logged Population | 0.45566*** | 0.51516*** | 0.53899*** | 0.50161*** | 0.46748*** | 0.49108*** | 0.46906*** |
| % Young People | 0.00404*** | 0.00102 | 0.00038 | 0.00200 | -0.00363 | -0.00028 | 0.00234 |
| Ethnic Heterogeneity | 0.00220* | 0.00067 | -0.00068 | 0.00029 | -0.00096 | -0.00116 | -0.00035 |
| % Low-income | 0.00338*** | 0.00399*** | 0.00249** | 0.00153 | 0.00103 | 0.00079 | 0.00461** |

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Table .9 – *Continued from previous page*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.02905*** | 0.01029 | 0.01366*** | 0.00545 | 0.02410*** | 0.01757*** | -0.01036 |
| % Residential LU | 0.01458*** | 0.00749** | 0.01882*** | 0.01874*** | 0.02042*** | 0.01827*** | 0.01249*** |
| % Retail LU | 0.02757*** | 0.01766* | 0.02555*** | 0.02823*** | 0.01866* | 0.02182*** | 0.01544* |
| % Office LU | -0.08513*** | -0.07927*** | -0.03403** | -0.03565* | -0.11708*** | -0.04403** | -0.01104 |
| % School LU | 0.05216*** | 0.05503** | -0.00788 | -0.03774** | 0.03158 | 0.00672 | -0.02678 |
| # of bars | -0.00014 | -0.00131 | 0.00122 | 0.00251* | 0.00267 | 0.00223* | 0.00660*** |
| # of grocery stores | 0.00093 | -0.00284** | -0.00250*** | -0.00118 | -0.00207 | -0.00283*** | -0.00191 |
| # of restaurants | -0.00047 | -0.00019 | 0.00001 | 0.00021 | -0.00031 | 0.00012 | 0.00025 |
| **Housing** | | | | | | | |
| % Homeowners | -0.00546 | 0.00767 | -0.00028 | -0.00317 | -0.01253** | -0.00108 | 0.00355 |
| % Vacant Units | 0.04664*** | 0.03462** | 0.02092*** | 0.02437** | 0.01625 | 0.01588* | 0.02421* |
| **Time Varying** | | | | | | | |
| Logged Population | 0.13444 | 0.41193*** | 0.02503 | -0.08953 | 0.02744 | 0.06603 | 0.26244 |
| % Young People | -0.00462 | -0.01213 | 0.00611 | 0.00167 | -0.01088 | -0.00494 | 0.00656 |
| Ethnic Heterogeneity | -0.00639*** | 0.00171 | 0.00044 | -0.00092 | -0.00123 | -0.00026 | -0.00373 |
| % Low-income | 0.03375*** | 0.04110*** | 0.03952*** | 0.03846*** | 0.04206*** | 0.04301*** | 0.04094*** |
| Intercept | -15.83032*** | -18.78806*** | -14.09489*** | -13.45851*** | -13.81504*** | -14.16469*** | -17.51032*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .10: Spring Robbery

| | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00669*** | -0.00671** | -0.00425** | -0.00165 | -0.00354 | -0.00345 | -0.00109 |
| % Residential LU | -0.00792*** | -0.01136*** | -0.01206*** | -0.01091*** | -0.01257*** | -0.01080*** | -0.01042*** |
| % Retail LU | 0.01030*** | 0.00686*** | 0.01148*** | 0.01148*** | 0.01370*** | 0.01286*** | 0.00698*** |
| % Office LU | -0.00692** | -0.00651* | 0.00000 | -0.00042 | 0.00103 | 0.00061 | 0.00308 |
| % School LU | -0.00193 | 0.00576** | 0.00068 | -0.00163 | 0.00011 | 0.00145 | -0.00374 |
| # of bars | 0.01143 | -0.11857 | 0.11102 | 0.32715*** | -0.07174 | 0.21197** | 0.40128*** |
| # of grocery stores | 0.39695*** | 0.47384*** | 0.42054*** | 0.35933*** | 0.40404*** | 0.43508*** | 0.50460*** |
| # of restaurants | 0.18521*** | 0.11772*** | 0.18426*** | 0.17916*** | 0.19313*** | 0.14271*** | 0.16256*** |
| **Housing** | | | | | | | |
| % Homeowners | -0.00690*** | -0.00350*** | -0.00671*** | -0.00746*** | -0.00623*** | -0.00824*** | -0.00787*** |
| % Vacant Units | 0.00883*** | 0.00836*** | 0.00877*** | 0.00879*** | 0.01134*** | 0.01031*** | 0.00856*** |
| **Time Varying** | | | | | | | |
| Logged Population | 0.44341*** | 0.46791*** | 0.48011*** | 0.51297*** | 0.46788*** | 0.50614*** | 0.44967*** |
| % Young People | 0.00532*** | -0.00076 | -0.00263* | 0.00216 | 0.00068 | -0.00236 | 0.00401* |
| Ethnic Heterogeneity | 0.00254** | 0.00184 | -0.00000 | 0.00054 | -0.00231 | -0.00268** | -0.00193 |
| % Low-income | 0.00244*** | 0.00623*** | 0.00218** | 0.00269** | -0.00112 | 0.00184 | 0.00460*** |

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Table .10 – *Continued from previous page*

| | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.02252*** | 0.02062*** | 0.01565*** | 0.01430*** | 0.01551** | 0.00371 | 0.01716** |
| % Residential LU | 0.01264*** | 0.01484*** | 0.01922*** | 0.02194*** | 0.01839*** | 0.01885*** | 0.02217*** |
| % Retail LU | 0.02358*** | 0.01173 | 0.02523*** | 0.02703*** | 0.02712*** | 0.02291*** | 0.02702*** |
| % Office LU | -0.08142*** | -0.04726** | -0.05794*** | -0.04414*** | -0.07269*** | -0.04318** | -0.00018 |
| % School LU | 0.01925 | 0.05758*** | 0.00205 | -0.01042 | 0.01564 | -0.02367 | -0.04517* |
| # of bars | 0.00060 | 0.00255 | 0.00116 | 0.00555*** | 0.00429** | 0.00191 | 0.00764*** |
| # of grocery stores | 0.00091 | -0.00294** | -0.00348*** | -0.00163* | -0.00180 | -0.00143 | -0.00190 |
| # of restaurants | -0.00070** | -0.00087** | 0.00036* | -0.00010 | -0.00022 | 0.00016 | -0.00012 |
| **Housing** | | | | | | | |
| % Homeowners | 0.00083 | -0.00226 | 0.00191 | -0.00434 | 0.00885* | 0.00199 | 0.00126 |
| % Vacant Units | 0.05196*** | 0.02037* | 0.02727*** | 0.02697*** | 0.02431* | 0.03219*** | 0.01623 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.30057*** | 0.52553*** | 0.15540 | -0.10607 | 0.21501 | -0.01818 | 0.16794 |
| % Young People | -0.00510 | -0.02501** | -0.00175 | 0.00347 | -0.00659 | 0.00448 | 0.01469* |
| Ethnic Heterogeneity | -0.00788*** | -0.00545* | -0.00152 | -0.00387** | -0.00003 | -0.00127 | -0.00358 |
| % Low-income | 0.03935*** | 0.03661*** | 0.04614*** | 0.04205*** | 0.05898*** | 0.04023*** | 0.04416*** |
| Intercept | -17.77668*** | -18.73428*** | -15.44742*** | -13.35672*** | -17.50593*** | -13.63918*** | -16.46374*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: LU = Land Use. Table is unstandardized coefficients.*

Table .11: Summer Robbery

| | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|
| | 7am-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | |
| % Industrial LU | -0.00715*** | -0.00167 | -0.00105 | -0.00055 | 0.00003 | 0.00248 |
| % Residential LU | -0.00947*** | -0.01101*** | -0.01029*** | -0.01222*** | -0.01113*** | -0.01188*** |
| % Retail LU | 0.00974*** | 0.01201*** | 0.01111*** | 0.01209*** | 0.00916*** | 0.01046*** |
| % Office LU | -0.00415* | -0.00178 | 0.00144 | 0.00470 | -0.00541* | 0.00079 |
| % School LU | -0.00762*** | 0.00374* | -0.00131 | -0.00004 | -0.00238 | -0.00111 |
| # of bars | 0.00244 | 0.01492 | 0.27987*** | 0.14719 | 0.03095 | 0.24418** |
| # of grocery stores | 0.46169*** | 0.42788*** | 0.38891*** | 0.38590*** | 0.38625*** | |
| # of restaurants | 0.16443*** | 0.22018*** | 0.19227*** | 0.19049*** | 0.19987*** | 0.13126*** |
| **Housing** | | | | | | |
| % Homeowners | -0.00530*** | -0.00741*** | -0.00781*** | -0.00630*** | -0.00829*** | -0.00685*** |
| % Vacant Units | 0.00893*** | 0.00810*** | 0.00934*** | 0.00605*** | 0.00940*** | 0.00977*** |
| **Time Varying** | | | | | | |
| Logged Population | 0.41792*** | 0.50255*** | 0.48349*** | 0.48816*** | 0.47913*** | 0.50070*** |
| % Young People | 0.00323*** | -0.00521*** | -0.00073 | -0.00695*** | -0.00238 | 0.00064 |
| Ethnic Heterogeneity | 0.00335*** | 0.00063 | 0.00176* | 0.00023 | -0.00134 | -0.00175 |
| % Low-income | 0.00274*** | 0.00325*** | 0.00200* | 0.00439*** | 0.00105 | 0.00290* |

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Table .11 – *Continued from previous page*

| | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|
| | 7am-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | |
| **Land Use and Business** | | | | | | |
| % Industrial LU | 0.02706*** | 0.01111** | 0.01277*** | 0.01461* | 0.01306** | 0.00488 |
| % Residential LU | 0.01667*** | 0.01827*** | 0.02344*** | 0.01515*** | 0.02127*** | 0.01581*** |
| % Retail LU | 0.02069*** | 0.02572*** | 0.02732*** | 0.01800** | 0.02651*** | 0.02088*** |
| % Office LU | -0.07208*** | -0.05844*** | -0.03833*** | -0.07694*** | -0.03981** | -0.04156* |
| % School LU | 0.05476*** | 0.00516 | -0.03339** | -0.00059 | 0.01009 | -0.03864* |
| # of bars | -0.00048 | 0.00052 | 0.00468*** | 0.00130 | 0.00100 | 0.00773*** |
| # of grocery stores | -0.00033 | -0.00323*** | -0.00224*** | -0.00268** | -0.00408*** | -0.00283** |
| # of restaurants | -0.00026 | 0.00017 | 0.00003 | 0.00017 | 0.00048* | -0.00012 |
| **Housing** | | | | | | |
| % Homeowners | -0.00534* | 0.00359 | -0.00832*** | 0.00400 | 0.00403 | -0.00175 |
| % Vacant Units | 0.04676*** | 0.03813*** | 0.02860*** | 0.04121*** | 0.03291*** | 0.02000* |
| **Time Varying** | | | | | | |
| Logged Population | 0.24080*** | 0.20382* | -0.20480* | 0.24269 | 0.22891* | 0.16112 |
| % Young People | -0.01359** | 0.00045 | 0.01179** | -0.00229 | -0.00554 | 0.00772 |
| Ethnic Heterogeneity | -0.00724*** | -0.00468*** | -0.00333** | -0.00310 | -0.00282 | -0.00298 |
| % Low-income | 0.03958*** | 0.04168*** | 0.04390*** | 0.04275*** | 0.04565*** | 0.04222*** |
| Intercept | -16.38132*** | -16.08813*** | -11.60894*** | -16.93084*** | -16.44555*** | -15.37055*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .12: Fall Robbery

| | 21 | 22 | 23 | 24 | 25 | 26 | 27 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00663*** | -0.00686** | -0.00129 | -0.00183 | -0.00295 | -0.00070 | -0.00028 |
| % Residential LU | -0.00846*** | -0.01190*** | -0.01133*** | -0.00929*** | -0.01216*** | -0.01043*** | -0.01039*** |
| % Retail LU | 0.00967*** | 0.01195*** | 0.01383*** | 0.01104*** | 0.01768*** | 0.01275*** | 0.01065*** |
| % Office LU | -0.00249 | -0.00817* | 0.00440* | 0.00140 | -0.00009 | -0.00310 | 0.00357 |
| % School LU | -0.00673*** | 0.00645** | 0.00208 | -0.00088 | 0.00142 | 0.00278 | -0.00304 |
| # of bars | 0.11798 | 0.10575 | 0.12048 | 0.16886* | 0.09992 | 0.30788*** | 0.33692*** |
| # of grocery stores | 0.42432*** | 0.36815*** | 0.44655*** | 0.45212*** | 0.39804*** | 0.40737*** | 0.33117*** |
| # of restaurants | 0.17356*** | 0.09117*** | 0.18935*** | 0.20610*** | 0.18977*** | 0.18391*** | 0.14886*** |
| **Housing** | | | | | | | |
| % Homeowners | -0.00635*** | -0.00305** | -0.00626*** | -0.00957*** | -0.00655*** | -0.00821*** | -0.00979*** |
| % Vacant Units | 0.00827*** | 0.00904*** | 0.00825*** | 0.00759*** | 0.01096*** | 0.00566*** | 0.00947*** |
| **Time Varying** | | | | | | | |
| Logged Population | 0.44464*** | 0.46774*** | 0.48590*** | 0.46526*** | 0.50953*** | 0.47298*** | 0.50739*** |
| % Young People | 0.00569*** | 0.00191 | -0.00197 | 0.00197 | -0.00284 | -0.00115 | -0.00152 |
| Ethnic Heterogeneity | 0.00233* | 0.00127 | 0.00037 | 0.00097 | -0.00029 | -0.00148 | -0.00211 |
| % Low-income | 0.00185** | 0.00625*** | 0.00230** | 0.00439*** | 0.00146 | 0.00217* | 0.00030 |

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Table .12 – *Continued from previous page*

| | 21 | 22 | 23 | 24 | 25 | 26 | 27 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.02291*** | 0.00547 | 0.00684* | 0.00932* | 0.00968 | 0.01736*** | 0.01060 |
| % Residential LU | 0.01386*** | 0.00749** | 0.01636*** | 0.02370*** | 0.01667*** | 0.02304*** | 0.02372*** |
| % Retail LU | 0.02808*** | 0.02495*** | 0.01578*** | 0.02584*** | 0.02026** | 0.01827*** | 0.02592*** |
| % Office LU | -0.09728*** | -0.08154*** | -0.06514*** | -0.05920*** | -0.05397** | -0.04103** | -0.00913 |
| % School LU | 0.03939** | 0.07213*** | 0.00337 | -0.05736*** | 0.02686 | 0.01906 | -0.02394 |
| # of bars | -0.00062 | -0.00047 | 0.00005 | 0.00228** | 0.00160 | 0.00097 | 0.01002*** |
| # of grocery stores | 0.00071 | -0.00324*** | -0.00300*** | -0.00104 | -0.00144 | -0.00235** | -0.00082 |
| # of restaurants | -0.00069** | -0.00041 | 0.00018 | 0.00070*** | -0.00016 | 0.00029 | -0.00030 |
| **Housing** | | | | | | | |
| % Homeowners | -0.00352 | -0.00472 | -0.00276 | -0.00066 | 0.01079** | -0.00078 | 0.00321 |
| % Vacant Units | 0.04279*** | -0.00033 | 0.03258*** | 0.03632*** | 0.02846** | 0.02181** | -0.00423 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.37913*** | 0.56618*** | 0.25039** | -0.28754** | 0.22612 | 0.02701 | -0.02190 |
| % Young People | -0.02881*** | -0.04511*** | -0.00129 | 0.01756*** | 0.00829 | -0.00138 | 0.02408*** |
| Ethnic Heterogeneity | -0.00498** | -0.00749*** | -0.00176 | -0.00377** | 0.00156 | -0.00006 | -0.00361 |
| % Low-income | 0.03692*** | 0.04071*** | 0.03717*** | 0.03609*** | 0.04665*** | 0.04090*** | 0.04936*** |
| Intercept | -17.83423*** | -17.89450*** | -15.84727*** | -11.47498*** | -17.79736*** | -13.88026*** | -14.47375*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .13: Winter Homicide

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.00026 | 0.00807 | -0.00209 | 0.00305 | -0.01334 | 0.00386 | 0.02136** |
| % Residential LU | -0.00597 | -0.00615 | -0.00534 | -0.00944* | -0.01520** | -0.00674 | 0.00058 |
| % Retail LU | -0.00062 | 0.00362 | 0.00613 | 0.00350 | 0.00698 | -0.00285 | -0.00151 |
| % Office LU | -0.02104 | -0.02270 | -0.01048 | -0.03042 | -0.01609 | -0.07519 | 0.02157* |
| % School LU | 0.00358 | -0.02013 | -0.01045 | -0.04145 | -0.05495 | -0.02470 | -0.00661 |
| # of bars | 0.54513 | | | 0.38411 | | 0.97716** | 0.76818* |
| # of grocery stores | 0.49801 | 0.62881 | 0.16034 | 0.20215 | -0.54628 | -0.64944 | 0.08052 |
| # of restaurants | 0.13889 | -0.55857 | 0.05077 | 0.15682 | 0.21633 | 0.05157 | 0.09357 |
| **Housing** | | | | | | | |
| % Homeowners | -0.00115 | -0.00795 | -0.01367*** | -0.00236 | -0.00733 | -0.01323** | -0.02129*** |
| % Vacant Units | 0.01793* | 0.01641 | 0.00628 | 0.01184 | 0.02211 | 0.00822 | 0.01663* |
| **Time Varying** | | | | | | | |
| Logged Population | 0.32104** | 0.54099** | 0.58330*** | 0.65719*** | 0.81599*** | 0.65233*** | 0.38962*** |
| % Young People | -0.00277 | 0.01149 | 0.00872 | 0.00669 | -0.02279 | -0.00170 | -0.02735* |
| Ethnic Heterogeneity | -0.00095 | -0.01536 | 0.00268 | -0.00934 | 0.00307 | -0.00159 | 0.00422 |
| % Low-income | 0.00252 | 0.01752* | -0.00027 | 0.01467* | 0.01024 | 0.00989 | 0.00808 |

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Table .13 – *Continued from previous page*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.02395 | -0.07519 | -0.00983 | 0.03317 | 0.04935 | 0.04337 | -0.04700 |
| % Residential LU | -0.00466 | -0.00081 | -0.01729 | 0.00797 | 0.03779 | 0.01808 | -0.01624 |
| % Retail LU | -0.06100 | -0.00892 | -0.00006 | 0.02767 | 0.02293 | 0.02992 | 0.01032 |
| % Office LU | 0.15331* | 0.18019 | -0.05476 | -0.24649** | 0.13753 | -0.13849 | -0.00804 |
| % School LU | 0.15152* | -0.21549 | -0.04709 | 0.03055 | -0.09743 | 0.15886 | -0.11244 |
| # of bars | 0.00187 | -0.01501 | 0.00050 | -0.00477 | 0.00330 | 0.00564 | 0.00131 |
| # of grocery stores | 0.00792 | -0.00414 | -0.00525 | 0.00026 | 0.01035 | 0.00158 | 0.00306 |
| # of restaurants | -0.00413** | 0.00365 | -0.00262 | 0.00094 | -0.00378 | -0.00129 | -0.00196 |
| **Housing** | | | | | | | |
| % Homeowners | -0.02646 | 0.05092 | 0.00001 | 0.00098 | 0.01399 | -0.01391 | 0.02728 |
| % Vacant Units | 0.03173 | -0.01902 | 0.07896* | 0.07881 | -0.00818 | 0.04774 | 0.04293 |
| **Time Varying** | | | | | | | |
| Logged Population | -0.33278 | 0.17305 | 1.05615* | -0.24542 | -0.98463 | -0.23569 | 0.92486 |
| % Young People | -0.01490 | 0.09895 | -0.04853 | -0.04948 | 0.07908 | -0.05067 | 0.06237 |
| Ethnic Heterogeneity | 0.01645 | -0.00339 | -0.00881 | 0.00697 | -0.02179 | 0.00314 | -0.00677 |
| % Low-income | 0.03554 | 0.07411* | 0.03914* | -0.00471 | 0.05329 | 0.02549 | 0.03115 |
| Intercept | -12.93424* | -24.25185** | -26.75765*** | -14.98056* | -10.13562 | -14.42417* | -27.78125*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .14: Spring Homicide

| | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00473 | 0.00192 | 0.00219 | 0.01092 | -0.00080 | -0.02843 | 0.00376 |
| % Residential LU | -0.00324 | -0.01326** | -0.00823** | -0.00657* | -0.00460 | -0.01096*** | -0.00812* |
| % Retail LU | 0.00180 | 0.00500 | 0.00629 | 0.00626 | -0.00162 | -0.00868 | 0.00201 |
| % Office LU | -0.00799 | 0.00373 | -0.00850 | 0.01414 | 0.00560 | -0.02300 | -0.00152 |
| % School LU | -0.00753 | -0.00943 | 0.00376 | 0.00569 | 0.00318 | -0.00171 | -0.02970 |
| # of bars | -0.04074 | 0.73903 | -1.32572 | 0.02296 | | 0.27139 | 1.11123*** |
| # of grocery stores | 0.29658 | 0.03959 | -0.06473 | -0.13401 | -0.06612 | -0.39895 | -0.43230 |
| # of restaurants | 0.13440 | 0.01879 | 0.14964 | 0.23751** | -0.41525 | 0.12615 | 0.07573 |
| **Housing** | | | | | | | |
| % Homeowners | -0.01330*** | -0.00796 | -0.00229 | -0.00580 | -0.00566 | -0.00936* | -0.00803 |
| % Vacant Units | 0.00942 | 0.01290 | 0.01541** | 0.01390* | 0.01572 | 0.00396 | 0.01695* |
| **Time Varying** | | | | | | | |
| Logged Population | 0.40077*** | 0.69588*** | 0.58526*** | 0.48019*** | 0.74836*** | 0.58279*** | 0.79201*** |
| % Young People | 0.00153 | 0.00802 | -0.00002 | -0.00284 | 0.01152 | -0.00017 | 0.00602 |
| Ethnic Heterogeneity | -0.00424 | -0.01369 | 0.00107 | -0.01369** | 0.00584 | 0.00053 | -0.00615 |
| % Low-income | 0.00680 | 0.00698 | 0.00515 | 0.01029* | 0.01023 | 0.01223* | 0.00253 |

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Table .14 – *Continued from previous page*

| | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.03932 | -0.00220 | -0.01734 | 0.02158 | 0.05615* | 0.03663 | 0.02119 |
| % Residential LU | 0.01846 | 0.00343 | -0.00381 | 0.01332 | 0.03733** | 0.02046 | -0.01357 |
| % Retail LU | 0.06512*** | -0.10790 | -0.00267 | 0.03946** | 0.03590 | 0.00785 | 0.01156 |
| % Office LU | -0.03479 | -0.13613 | 0.01298 | -0.22174* | 0.00670 | -0.09981 | -0.00069 |
| % School LU | 0.10745 | 0.04728 | -0.04921 | 0.06850 | 0.04593 | 0.04901 | -0.00218 |
| # of bars | -0.00339 | -0.00208 | -0.00055 | -0.00841 | 0.01529 | -0.01462 | -0.00290 |
| # of grocery stores | 0.00470 | -0.00735 | -0.00286 | -0.00697 | 0.00499 | 0.00169 | -0.00654 |
| # of restaurants | -0.00089 | -0.00006 | -0.00141 | 0.00106 | -0.00529* | 0.00107 | -0.00084 |
| **Housing** | | | | | | | |
| % Homeowners | 0.00731 | 0.00627 | 0.00058 | 0.00382 | -0.00197 | 0.00922 | 0.02910 |
| % Vacant Units | 0.08319* | 0.04674 | 0.05726 | 0.05249 | 0.06703 | 0.00901 | 0.07678 |
| **Time Varying** | | | | | | | |
| Logged Population | -0.29798 | 0.58323 | 0.75791 | 0.37092 | -0.54285 | -0.32937 | 1.70805** |
| % Young People | -0.06154 | -0.06309 | 0.01875 | -0.05204 | -0.03636 | -0.02211 | -0.04194 |
| Ethnic Heterogeneity | 0.01019 | 0.00582 | -0.01082 | 0.00752 | -0.00232 | -0.00453 | 0.00090 |
| % Low-income | 0.01682 | 0.04395 | 0.05857** | 0.04639* | 0.03958 | 0.03184 | 0.05223* |
| Intercept | -14.41357** | -22.95305** | -26.45886*** | -21.63370*** | -14.02459* | -13.35195* | -37.86200*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: LU = Land Use. Table is unstandardized coefficients.*

Table .15: Summer Homicide

| | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|
| | 7am-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | |
| % Industrial LU | 0.00284 | 0.01151 | -0.01568 | 0.00675 | 0.00110 | -0.00756 |
| % Residential LU | -0.00163 | -0.00296 | -0.00945*** | -0.00618 | -0.01010** | -0.00426 |
| % Retail LU | 0.00700 | 0.00666 | 0.01019 | -0.00234 | 0.00566 | 0.01065 |
| % Office LU | -0.00554 | 0.00416 | -0.00104 | -0.01436 | -0.01365 | 0.00794 |
| % School LU | -0.00980 | 0.00644 | -0.01431 | -0.00342 | -0.02710 | -0.00279 |
| # of bars | -0.56867 | -0.15828 | -0.13863 | 0.12203 | 0.10072 | 0.62675 |
| # of grocery stores | 0.35023 | 0.11611 | 0.35839* | 0.47584 | 0.21303 | 0.36340 |
| # of restaurants | 0.10848 | -0.06498 | 0.06060 | 0.17460 | -0.02534 | 0.01756 |
| **Housing** | | | | | | |
| % Homeowners | -0.00731* | -0.00919** | -0.00633* | -0.00277 | -0.00839* | -0.00075 |
| % Vacant Units | 0.00785 | 0.01338* | 0.01066 | 0.01445 | 0.01149 | 0.00967 |
| **Time Varying** | | | | | | |
| Logged Population | 0.39792*** | 0.65589*** | 0.67259*** | 0.72558*** | 0.56759*** | 0.64081*** |
| % Young People | 0.00284 | 0.00108 | -0.00887 | 0.00369 | 0.01183 | 0.00631 |
| Ethnic Heterogeneity | 0.00060 | -0.00490 | -0.00715 | 0.00075 | -0.01279* | 0.00250 |
| % Low-income | -0.00287 | 0.00329 | 0.00687 | 0.00123 | 0.00456 | 0.00804 |

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Table .15 – *Continued from previous page*

| | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|
| | 7am-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | |
| **Land Use and Business** | | | | | | |
| % Industrial LU | 0.01599 | 0.03228 | 0.03639* | 0.02535 | 0.00614 | 0.05609* |
| % Residential LU | 0.01877* | 0.02588** | 0.02045* | -0.01231 | 0.01808 | 0.01153 |
| % Retail LU | 0.03433 | 0.00390 | 0.02120 | 0.00554 | 0.03960* | 0.03504 |
| % Office LU | 0.00292 | -0.02219 | -0.07511 | -0.21341 | -0.00447 | -0.02599 |
| % School LU | -0.06066 | -0.01757 | -0.00887 | 0.00212 | 0.03947 | 0.06939 |
| # of bars | -0.00095 | 0.00020 | 0.00169 | -0.00858 | -0.00190 | 0.00903 |
| # of grocery stores | 0.00193 | 0.00488 | 0.00263 | -0.00028 | 0.00690* | -0.00272 |
| # of restaurants | -0.00234 | -0.00171 | -0.00167 | -0.00268 | -0.00202 | -0.00176 |
| **Housing** | | | | | | |
| % Homeowners | 0.00388 | 0.00617 | 0.01859 | -0.01635 | 0.00159 | 0.01778 |
| % Vacant Units | 0.09790** | 0.03853 | 0.08242** | 0.06260 | 0.02337 | 0.11997** |
| **Time Varying** | | | | | | |
| Logged Population | 0.10925 | -0.28663 | 0.04664 | 0.57595 | -0.50335 | 0.78342 |
| % Young People | 0.01010 | -0.01837 | 0.05316* | -0.02657 | -0.02834 | -0.02165 |
| Ethnic Heterogeneity | -0.00226 | 0.00498 | 0.00084 | 0.01287 | 0.00661 | 0.00023 |
| % Low-income | 0.04226** | 0.05634** | 0.02699 | 0.04070 | 0.03290 | 0.06174** |
| Intercept | -19.61486*** | -16.38743*** | -20.88251*** | -23.12571** | -11.32436* | -29.77199*** |

$*p < .05; **p < .01; ***p < .001$

*Note:*

Table .16: Fall Homicide

| | 21 | 22 | 23 | 24 | 25 | 26 | 27 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00590 | 0.00601 | -0.00268 | -0.00687 | 0.00345 | -0.01330 | -0.00786 |
| % Residential LU | -0.00612 | 0.00847 | -0.00543 | -0.00471 | -0.01067** | -0.00781* | -0.00879** |
| % Retail LU | -0.00977 | 0.00893 | 0.01123 | 0.00851 | 0.00037 | 0.00372 | 0.00869 |
| % Office LU | 0.01281 | 0.01669 | -0.02091 | 0.01226 | -0.08743 | -0.01079 | 0.00177 |
| % School LU | -0.02665 | -0.00015 | 0.00875 | -0.00106 | -0.01741 | 0.00963 | 0.01021 |
| # of bars | 0.50437 | 0.89538 | 0.47153 | 0.86345* | -0.26730 | 0.75193* | 0.61613 |
| # of grocery stores | 0.31547 | 0.80803* | 0.23807 | 0.06218 | 0.23525 | 0.36924 | 0.08146 |
| # of restaurants | 0.09412 | 0.05697 | 0.00021 | -0.13627 | -0.05490 | -0.08626 | 0.13252 |
| **Housing** | | | | | | | |
| % Homeowners | -0.00635 | -0.00998 | -0.00548 | -0.01402** | -0.00565 | -0.01378** | -0.00716 |
| % Vacant Units | 0.01386* | -0.00232 | 0.01898** | 0.00501 | 0.00519 | 0.00078 | 0.00938 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.47618*** | 0.23088 | 0.73646*** | 0.67159*** | 0.53069*** | 0.58727*** | 0.59864*** |
| % Young People | 0.00126 | 0.00290 | 0.00305 | -0.01013 | 0.01990* | 0.00320 | 0.01512 |
| Ethnic Heterogeneity | -0.00096 | -0.00599 | -0.01132* | -0.00305 | -0.00485 | -0.01050 | -0.00875 |
| % Low-income | 0.00313 | 0.01807* | 0.00802 | -0.00504 | 0.01065 | 0.00516 | 0.00631 |

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Table .16 – *Continued from previous page*

| | 21 | 22 | 23 | 24 | 25 | 26 | 27 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.02964 | -0.00268 | 0.01079 | 0.01421 | 0.06910** | 0.00696 | 0.01192 |
| % Residential LU | 0.01479 | -0.00298 | 0.01357 | 0.00865 | 0.00549 | 0.00094 | 0.00236 |
| % Retail LU | -0.01311 | -0.07015 | 0.01003 | 0.02050 | -0.02260 | 0.03782* | -0.01294 |
| % Office LU | 0.06841 | 0.11019 | -0.05125 | -0.15208 | 0.03411 | 0.10222 | 0.01649 |
| % School LU | 0.09162 | -0.05892 | 0.03859 | -0.04370 | 0.13762 | -0.01572 | -0.15109 |
| # of bars | -0.00200 | -0.04502* | 0.00589 | -0.00808 | -0.00277 | 0.00082 | 0.01067 |
| # of grocery stores | 0.00731* | 0.00123 | 0.00100 | 0.00359 | 0.00046 | -0.00278 | -0.00420 |
| # of restaurants | -0.00283* | 0.00110 | -0.00093 | -0.00069 | -0.00155 | -0.00031 | -0.00427** |
| **Housing** | | | | | | | |
| % Homeowners | -0.01312 | -0.00018 | -0.00153 | 0.00093 | 0.02222 | 0.06130*** | 0.00232 |
| % Vacant Units | 0.08464* | -0.00793 | -0.01611 | 0.03331 | 0.07256 | 0.09114* | -0.02690 |
| **Time Varying** | | | | | | | |
| Logged Population | -0.09337 | 0.40704 | -0.02469 | 0.22154 | 0.97387 | 0.60735 | 1.57096* |
| % Young People | -0.01353 | -0.05163 | -0.07375* | -0.01977 | -0.05122 | 0.00571 | -0.00412 |
| Ethnic Heterogeneity | -0.00562 | 0.02299 | 0.00191 | -0.00337 | 0.03398** | -0.00342 | 0.00403 |
| % Low-income | 0.01585 | 0.02190 | 0.05497** | 0.03078 | 0.04671 | 0.05704** | 0.05630* |
| Intercept | -15.93073** | -19.44351* | -16.78035** | -19.46368** | -31.92326*** | -28.00921*** | -33.98213*** |

$*p < .05; **p < .01; ***p < .001$

*Note:*

Table .17: Winter Larceny

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00263*** | -0.00285* | 0.00427*** | 0.00588*** | 0.00605*** | 0.00273** | 0.00318 |
| % Residential LU | -0.00692*** | -0.00987*** | -0.00977*** | -0.00761*** | -0.01108*** | -0.01018*** | -0.00935*** |
| % Retail LU | 0.00850*** | 0.01166*** | 0.01312*** | 0.00793*** | 0.01598*** | 0.01408*** | 0.01090*** |
| % Office LU | -0.00127 | -0.00520** | 0.00261* | 0.00313* | 0.00531*** | 0.00307* | -0.00131 |
| % School LU | -0.00335*** | 0.00772*** | 0.00118 | 0.00147 | 0.00140 | 0.00051 | -0.00234 |
| # of bars | 0.10816** | 0.04507 | 0.25272*** | 0.39801*** | 0.12496* | 0.38005*** | 0.66227*** |
| # of grocery stores | 0.32262*** | 0.38454*** | 0.40869*** | 0.34688*** | 0.37144*** | 0.41447*** | 0.30097*** |
| # of restaurants | 0.16792*** | 0.21012*** | 0.25261*** | 0.15681*** | 0.25484*** | 0.22443*** | 0.14777*** |
| **Housing** | | | | | | | |
| % Homeowners | -0.00210*** | -0.00086 | -0.00311*** | -0.00343*** | -0.00418*** | -0.00404*** | -0.00355*** |
| % Vacant Units | 0.00704*** | 0.00742*** | 0.00528*** | 0.00440*** | 0.00569*** | 0.00583*** | 0.00562*** |
| **Time Varying** | | | | | | | |
| Logged Population | 0.54777*** | 0.62371*** | 0.57741*** | 0.58012*** | 0.53401*** | 0.57303*** | 0.56555*** |
| % Young People | 0.00334*** | 0.00227** | 0.00028 | 0.00127 | -0.00053 | -0.00166 | 0.00517*** |
| Ethnic Heterogeneity | 0.00280*** | 0.00301*** | 0.00244*** | 0.00297*** | 0.00067 | 0.00177** | 0.00232* |
| % Low-income | 0.00165*** | 0.00338*** | -0.00052 | 0.00045 | -0.00053 | -0.00097 | 0.00000 |

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Table .17 – *Continued from previous page*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.00520** | -0.00092 | 0.00895*** | -0.00080 | 0.00567* | 0.01030*** | 0.00664 |
| % Residential LU | 0.00688*** | 0.00623*** | 0.01240*** | 0.00896*** | 0.01384*** | 0.01093*** | 0.01344*** |
| % Retail LU | 0.01332*** | 0.01718*** | 0.02188*** | 0.01648*** | 0.01888*** | 0.02018*** | 0.02357*** |
| % Office LU | -0.02240*** | -0.03268*** | -0.02399*** | -0.02906*** | -0.02311** | -0.02678*** | -0.01940 |
| % School LU | 0.01768*** | 0.00616 | 0.00063 | -0.00862 | 0.00314 | -0.01774** | -0.01510 |
| # of bars | 0.00235*** | 0.00196** | 0.00338*** | 0.00255*** | 0.00227*** | 0.00432*** | 0.00715*** |
| # of grocery stores | -0.00238*** | -0.00438*** | -0.00368*** | -0.00325*** | -0.00289*** | -0.00344*** | -0.00380*** |
| # of restaurants | -0.00001 | 0.00054*** | 0.00045*** | 0.00040*** | 0.00078*** | 0.00055*** | 0.00037 |
| **Housing** | | | | | | | |
| % Homeowners | -0.00208 | -0.00182 | -0.00518*** | 0.00047 | 0.00188 | 0.00190 | 0.00319 |
| % Vacant Units | 0.04570*** | 0.04108*** | 0.03844*** | 0.04015*** | 0.05091*** | 0.05210*** | 0.04630*** |
| **Time Varying** | | | | | | | |
| Logged Population | 0.00810 | -0.00281 | -0.17155*** | -0.19424*** | -0.34356*** | -0.09349 | -0.20385* |
| % Young People | 0.00135 | 0.00203 | 0.01159*** | 0.01317*** | 0.01405*** | 0.01233*** | 0.01725*** |
| Ethnic Heterogeneity | -0.00174* | -0.00277* | -0.00017 | -0.00106 | 0.00025 | -0.00162 | -0.00229 |
| % Low-income | 0.00669*** | 0.00735*** | -0.00048 | 0.00783*** | 0.00964*** | 0.00168 | 0.01493*** |
| Intercept | -11.64240*** | -11.57152*** | -9.70453*** | -10.54280*** | -8.35284*** | -10.89259*** | -11.30412*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .18: Spring Larceny

| | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00146* | -0.00278* | 0.00443*** | 0.00399*** | 0.00537*** | 0.00407*** | 0.00241 |
| % Residential LU | -0.00697*** | -0.00995*** | -0.00930*** | -0.00728*** | -0.01182*** | -0.00961*** | -0.00925*** |
| % Retail LU | 0.00903*** | 0.01196*** | 0.01314*** | 0.00828*** | 0.01367*** | 0.01385*** | 0.00887*** |
| % Office LU | -0.00106 | -0.00268 | 0.00244* | 0.00353** | 0.00291* | 0.00296* | 0.00368 |
| % School LU | -0.00176* | 0.00818*** | 0.00196* | 0.00323** | 0.00252* | -0.00076 | -0.00642** |
| # of bars | 0.06175 | 0.04649 | 0.20085*** | 0.36761*** | 0.11700* | 0.37098*** | 0.53482*** |
| # of grocery stores | 0.32419*** | 0.38791*** | 0.36656*** | 0.33070*** | 0.32497*** | 0.39715*** | 0.31783*** |
| # of restaurants | 0.16866*** | 0.18106*** | 0.25254*** | 0.16062*** | 0.25616*** | 0.21933*** | 0.15440*** |
| **Housing** | | | | | | | |
| % Homeowners | -0.00246*** | -0.00096* | -0.00403*** | -0.00410*** | -0.00306*** | -0.00356*** | -0.00248*** |
| % Vacant Units | 0.00661*** | 0.00791*** | 0.00574*** | 0.00577*** | 0.00629*** | 0.00612*** | 0.00688*** |
| **Time Varying** | | | | | | | |
| Logged Population | 0.53418*** | 0.59011*** | 0.55255*** | 0.55698*** | 0.53935*** | 0.56668*** | 0.56743*** |
| % Young People | 0.00361*** | 0.00459*** | 0.00077 | 0.00146* | -0.00113 | 0.00134 | 0.00975*** |
| Ethnic Heterogeneity | 0.00271*** | 0.00378*** | 0.00196*** | 0.00332*** | 0.00091 | 0.00161** | 0.00259** |
| % Low-income | 0.00195*** | 0.00380*** | -0.00155*** | 0.00027 | -0.00053 | -0.00119* | -0.00036 |

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Table .18 – *Continued from previous page*

| | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.00489** | 0.00396 | 0.00660*** | 0.00698*** | 0.00320 | 0.00597** | 0.00710 |
| % Residential LU | 0.00751*** | 0.00880*** | 0.01135*** | 0.01050*** | 0.01143*** | 0.01139*** | 0.01078*** |
| % Retail LU | 0.01717*** | 0.01670*** | 0.02312*** | 0.01807*** | 0.01884*** | 0.01713*** | 0.01645*** |
| % Office LU | -0.02114*** | -0.02711*** | -0.02124*** | -0.03090*** | -0.02697*** | -0.03480*** | -0.01795 |
| % School LU | 0.01085* | -0.00117 | -0.00414 | -0.01166* | -0.00549 | -0.01301* | -0.03331** |
| # of bars | 0.00214*** | 0.00244*** | 0.00332*** | 0.00255*** | 0.00275*** | 0.00406*** | 0.00744*** |
| # of grocery stores | -0.00251*** | -0.00321*** | -0.00448*** | -0.00290*** | -0.00399*** | -0.00385*** | -0.00344*** |
| # of restaurants | 0.00013 | 0.00038** | 0.00055*** | 0.00046*** | 0.00071*** | 0.00066*** | 0.00005 |
| **Housing** | | | | | | | |
| % Homeowners | -0.00209* | -0.00171 | -0.00494*** | -0.00055 | -0.00233 | -0.00133 | 0.00326 |
| % Vacant Units | 0.04627*** | 0.04573*** | 0.03659*** | 0.04011*** | 0.04158*** | 0.04027*** | 0.04319*** |
| **Time Varying** | | | | | | | |
| Logged Population | -0.00249 | -0.08930* | -0.16135*** | -0.23419*** | -0.28783*** | -0.18536*** | -0.13463 |
| % Young People | -0.00134 | -0.00123 | 0.00705*** | 0.00805*** | 0.01289*** | 0.01035*** | 0.01280*** |
| Ethnic Heterogeneity | -0.00398*** | -0.00070 | -0.00025 | -0.00183* | -0.00032 | 0.00033 | -0.00061 |
| % Low-income | 0.00880*** | 0.00873*** | 0.00324* | 0.00886*** | 0.01370*** | 0.00729*** | 0.01727*** |
| Intercept | -11.13476*** | -10.54624*** | -9.20779*** | -9.67341*** | -8.25570*** | -9.51029*** | -11.77144*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: LU = Land Use. Table is unstandardized coefficients.*

Table .19: Summer Larceny

| | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|
| | 7am-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | |
| % Industrial LU | -0.00178** | 0.00437*** | 0.00522*** | 0.00411*** | 0.00708*** | 0.00256 |
| % Residential LU | -0.00674*** | -0.00924*** | -0.00769*** | -0.01138*** | -0.00963*** | -0.00885*** |
| % Retail LU | 0.01014*** | 0.01395*** | 0.01036*** | 0.01595*** | 0.01484*** | 0.01066*** |
| % Office LU | -0.00070 | 0.00455*** | 0.00258* | 0.00510*** | 0.00458*** | 0.00306 |
| % School LU | -0.00576*** | 0.00095 | -0.00006 | 0.00087 | -0.00068 | -0.00772*** |
| # of bars | 0.04351 | 0.23069*** | 0.41679*** | 0.13113** | 0.31512*** | 0.53140*** |
| # of grocery stores | 0.34981*** | 0.40409*** | 0.38659*** | 0.34347*** | 0.39120*** | |
| # of restaurants | 0.18916*** | 0.23358*** | 0.14655*** | 0.24396*** | 0.21667*** | 0.15349*** |
| **Housing** | | | | | | |
| % Homeowners | -0.00274*** | -0.00336*** | -0.00347*** | -0.00366*** | -0.00302*** | -0.00392*** |
| % Vacant Units | 0.00632*** | 0.00526*** | 0.00547*** | 0.00684*** | 0.00624*** | 0.00607*** |
| **Time Varying** | | | | | | |
| Logged Population | 0.51645*** | 0.56266*** | 0.58603*** | 0.54529*** | 0.55185*** | 0.57299*** |
| % Young People | 0.00281*** | -0.00061 | 0.00152* | -0.00230** | 0.00022 | 0.00460*** |
| Ethnic Heterogeneity | 0.00313*** | 0.00178*** | 0.00246*** | 0.00215*** | 0.00162** | 0.00276** |
| % Low-income | 0.00192*** | -0.00127** | -0.00098* | -0.00098 | -0.00182*** | 0.00202* |

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Table .19 – *Continued from previous page*

| | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|
| | 7am-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | |
| **Land Use and Business** | | | | | | |
| % Industrial LU | 0.00548*** | 0.00425* | 0.00592** | 0.00431 | 0.00675** | 0.00949** |
| % Residential LU | 0.00709*** | 0.01042*** | 0.00975*** | 0.01161*** | 0.00981*** | 0.01266*** |
| % Retail LU | 0.01169*** | 0.01821*** | 0.01598*** | 0.02043*** | 0.01908*** | 0.01471*** |
| % Office LU | -0.02529*** | -0.03078*** | -0.02967*** | -0.03908*** | -0.04051*** | -0.03516** |
| % School LU | 0.01754*** | -0.00848 | -0.00453 | -0.01377* | 0.00348 | -0.02200* |
| # of bars | 0.00167*** | 0.00306*** | 0.00263*** | 0.00263*** | 0.00421*** | 0.00667*** |
| # of grocery stores | -0.00252*** | -0.00485*** | -0.00371*** | -0.00371*** | -0.00489*** | -0.00365*** |
| # of restaurants | 0.00045*** | 0.00067*** | 0.00041*** | 0.00076*** | 0.00072*** | 0.00052** |
| **Housing** | | | | | | |
| % Homeowners | -0.00362*** | -0.00717*** | -0.00212 | -0.00102 | -0.00244 | 0.00305 |
| % Vacant Units | 0.04380*** | 0.03561*** | 0.04211*** | 0.04795*** | 0.04586*** | 0.03529*** |
| **Time Varying** | | | | | | |
| Logged Population | -0.06843** | -0.15641*** | -0.15620*** | -0.30054*** | -0.07685 | -0.19046* |
| % Young People | 0.00276 | 0.00724*** | 0.00783*** | 0.01581*** | 0.00584** | 0.00917** |
| Ethnic Heterogeneity | -0.00474*** | -0.00011 | -0.00098 | -0.00170* | -0.00008 | -0.00184 |
| % Low-income | 0.00643*** | 0.00251 | 0.00968*** | 0.01226*** | 0.00629*** | 0.01819*** |
| Intercept | -10.10304*** | -8.88173*** | -10.36551*** | -8.16191*** | -10.36752*** | -10.87224*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .20: Fall Larceny

| | 21 | 22 | 23 | 24 | 25 | 26 | 27 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.00017 | -0.00155 | 0.00361*** | 0.00547*** | 0.00488*** | 0.00511*** | 0.00269 |
| % Residential LU | -0.00671*** | -0.01012*** | -0.00929*** | -0.00750*** | -0.01203*** | -0.00914*** | -0.00859*** |
| % Retail LU | 0.00861*** | 0.01167*** | 0.01421*** | 0.00897*** | 0.01474*** | 0.01469*** | 0.01067*** |
| % Office LU | -0.00176 | -0.00216 | 0.00338*** | 0.00307* | 0.00291* | 0.00311* | 0.00325 |
| % School LU | -0.00051 | 0.00937*** | 0.00356*** | 0.00164 | -0.00008 | 0.00149 | -0.00406* |
| # of bars | 0.04810 | 0.10178 | 0.23715*** | 0.35858*** | 0.12868** | 0.36230*** | 0.71210*** |
| # of grocery stores | 0.34170*** | 0.37028*** | 0.40622*** | 0.37997*** | 0.39056*** | 0.40944*** | 0.37817*** |
| # of restaurants | 0.18440*** | 0.17369*** | 0.24901*** | 0.14952*** | 0.26855*** | 0.23025*** | 0.16067*** |
| **Housing** | | | | | | | |
| % Homeowners | -0.00275*** | -0.00089* | -0.00327*** | -0.00359*** | -0.00337*** | -0.00344*** | -0.00467*** |
| % Vacant Units | 0.00551*** | 0.00752*** | 0.00374*** | 0.00502*** | 0.00570*** | 0.00518*** | 0.00672*** |
| **Time Varying** | | | | | | | |
| Logged Population | 0.52079*** | 0.59636*** | 0.56106*** | 0.56758*** | 0.53384*** | 0.55230*** | 0.53121*** |
| % Young People | 0.00314*** | 0.00374*** | 0.00041 | 0.00112 | -0.00059 | 0.00078 | 0.00522*** |
| Ethnic Heterogeneity | 0.00273*** | 0.00409*** | 0.00222*** | 0.00234*** | 0.00167** | 0.00239*** | 0.00474*** |
| % Low-income | 0.00152*** | 0.00404*** | -0.00131** | -0.00105* | -0.00099 | -0.00030 | 0.00084 |

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Table .20 – *Continued from previous page*

| | 21 | 22 | 23 | 24 | 25 | 26 | 27 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.00306 | 0.00279 | 0.00872*** | 0.00549** | 0.00626* | 0.00844*** | 0.01173** |
| % Residential LU | 0.00623*** | 0.00863*** | 0.01075*** | 0.01183*** | 0.01192*** | 0.01134*** | 0.01001*** |
| % Retail LU | 0.01146*** | 0.01160*** | 0.01932*** | 0.01662*** | 0.01207*** | 0.01893*** | 0.01094** |
| % Office LU | -0.01783*** | -0.01811* | -0.02346*** | -0.01798** | -0.01959** | -0.03907*** | -0.05280*** |
| % School LU | 0.02738*** | 0.02441** | -0.00092 | 0.00100 | -0.00436 | -0.00597 | -0.01940 |
| # of bars | 0.00200*** | 0.00329*** | 0.00310*** | 0.00333*** | 0.00152** | 0.00431*** | 0.00640*** |
| # of grocery stores | -0.00254*** | -0.00328*** | -0.00391*** | -0.00308*** | -0.00360*** | -0.00306*** | -0.00390*** |
| # of restaurants | 0.00016 | 0.00036* | 0.00048*** | 0.00042*** | 0.00090*** | 0.00059*** | 0.00042* |
| **Housing** | | | | | | | |
| % Homeowners | -0.00119 | -0.00230 | -0.00452*** | -0.00186 | -0.00162 | -0.00180 | 0.00112 |
| % Vacant Units | 0.04232*** | 0.04137*** | 0.04274*** | 0.03903*** | 0.04816*** | 0.04803*** | 0.04268*** |
| **Time Varying** | | | | | | | |
| Logged Population | 0.01362 | -0.10974** | -0.04908 | -0.29417*** | -0.24264*** | -0.23126*** | -0.16417* |
| % Young People | 0.00387 | 0.00044 | 0.01029*** | 0.01183*** | 0.01977*** | 0.01577*** | 0.01848*** |
| Ethnic Heterogeneity | -0.00305*** | -0.00186 | -0.00047 | -0.00123 | -0.00244** | 0.00075 | -0.00146 |
| % Low-income | 0.00897*** | 0.00862*** | -0.00052 | 0.01042*** | 0.01034*** | 0.00268 | 0.01212*** |
| Intercept | -11.37463*** | -10.30648*** | -10.61162*** | -9.08685*** | -8.91844*** | -9.10087*** | -10.97248*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .21: Winter Motor Theft

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.00192 | 0.00147 | 0.00473*** | 0.00579*** | 0.00697*** | 0.00525*** | 0.00811*** |
| % Residential LU | -0.00276*** | -0.00500*** | -0.00457*** | -0.00564*** | -0.00797*** | -0.00579*** | -0.00477*** |
| % Retail LU | 0.00172 | 0.00029 | 0.00621*** | 0.00031 | 0.00840*** | 0.00519*** | 0.00126 |
| % Office LU | -0.00120 | -0.00947** | -0.00202 | -0.00066 | 0.00140 | -0.00273 | -0.00088 |
| % School LU | -0.01184*** | -0.00166 | -0.00339* | -0.00383* | 0.00112 | -0.00227 | -0.00419 |
| # of bars | 0.11287 | 0.00253 | 0.15589** | 0.20526** | 0.27383** | 0.34370*** | 0.33467** |
| # of grocery stores | 0.11237** | 0.01037 | 0.10470** | 0.07919 | 0.14684** | 0.14513*** | 0.09868 |
| # of restaurants | 0.08246*** | 0.12465*** | 0.12695*** | 0.09410*** | 0.14159*** | 0.12158*** | 0.13067*** |
| **Housing** | | | | | | | |
| % Homeowners | -0.00628*** | -0.00552*** | -0.00614*** | -0.00596*** | -0.00718*** | -0.00605*** | -0.00804*** |
| % Vacant Units | 0.00458*** | 0.00211 | 0.00248* | 0.00300* | 0.00487** | 0.00529*** | 0.00658** |
| **Time Varying** | | | | | | | |
| Logged Population | 0.54291*** | 0.64287*** | 0.67759*** | 0.65557*** | 0.59484*** | 0.64995*** | 0.60579*** |
| % Young People | 0.00371*** | 0.00205 | 0.00559*** | 0.00539*** | 0.00143 | 0.00295* | 0.00370 |
| Ethnic Heterogeneity | 0.00259*** | 0.00237 | -0.00022 | 0.00086 | -0.00112 | -0.00022 | 0.00232 |
| % Low-income | -0.00006 | 0.00320** | -0.00109 | -0.00092 | -0.00014 | -0.00075 | -0.00077 |

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Table .21 – *Continued from previous page*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.00871** | 0.01134* | 0.00777** | 0.00907** | 0.00967* | 0.01162*** | 0.01688** |
| % Residential LU | 0.00099 | 0.00412 | 0.00356** | 0.00509** | 0.00316 | 0.00671*** | 0.00766* |
| % Retail LU | 0.00842* | 0.01623** | 0.01186*** | 0.01405*** | 0.00710 | 0.00908* | 0.01177 |
| % Office LU | -0.04762*** | -0.00726 | -0.01840* | -0.04536*** | -0.05067*** | -0.02460* | -0.02301 |
| % School LU | -0.01053 | -0.01330 | -0.02789*** | -0.04313*** | -0.03089* | -0.03457** | -0.04273* |
| # of bars | -0.00054 | 0.00088 | 0.00211** | 0.00116 | 0.00035 | 0.00311*** | 0.00510** |
| # of grocery stores | -0.00188*** | -0.00204* | -0.00204*** | -0.00346*** | -0.00343*** | -0.00189** | -0.00239* |
| # of restaurants | -0.00067*** | -0.00064* | -0.00110*** | -0.00086*** | -0.00095*** | -0.00106*** | -0.00128*** |
| **Housing** | | | | | | | |
| % Homeowners | 0.00032 | -0.00737* | -0.00248 | 0.00709** | 0.00102 | -0.00077 | 0.00631 |
| % Vacant Units | 0.01421* | -0.02042 | -0.01040 | 0.02107** | -0.00447 | -0.00757 | 0.02063 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.28154*** | 0.03655 | 0.47486*** | 0.45295*** | 0.51716*** | 0.26937*** | 0.43351** |
| % Young People | 0.00189 | 0.00710 | 0.00123 | 0.00450 | 0.00749 | 0.00865 | -0.00030 |
| Ethnic Heterogeneity | -0.00462*** | -0.00806*** | -0.00349*** | -0.00364** | -0.00311 | -0.00062 | -0.00277 |
| % Low-income | 0.03725*** | 0.02435*** | 0.02021*** | 0.03053*** | 0.02488*** | 0.02715*** | 0.02919*** |
| Intercept | -16.00027*** | -12.51004*** | -17.64056*** | -19.13311*** | -18.29932*** | -15.90031*** | -19.01931*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .22: Spring Motor Theft

| | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.00337** | 0.00442* | 0.00382*** | 0.00215 | 0.01115*** | 0.00439** | 0.00397 |
| % Residential LU | -0.00303*** | -0.00366*** | -0.00555*** | -0.00458*** | -0.00669*** | -0.00491*** | -0.00447*** |
| % Retail LU | 0.00429*** | 0.00522** | 0.00393*** | 0.00304** | 0.00721*** | 0.00750*** | 0.00696*** |
| % Office LU | -0.00192 | -0.00129 | -0.00116 | -0.00284 | 0.00246 | -0.00057 | 0.00042 |
| % School LU | -0.00829*** | -0.00505 | -0.00214 | -0.00116 | 0.00323 | 0.00015 | -0.00327 |
| # of bars | 0.02365 | -0.06378 | 0.15444** | 0.15305* | 0.15527 | 0.33707*** | 0.42670*** |
| # of grocery stores | 0.18209*** | 0.10286 | 0.15985*** | 0.16076*** | 0.15635** | 0.12732** | 0.12238 |
| # of restaurants | 0.06190*** | 0.10582*** | 0.11234*** | 0.07611*** | 0.14940*** | 0.12250*** | 0.05587* |
| **Housing** | | | | | | | |
| % Homeowners | -0.00685*** | -0.00617*** | -0.00630*** | -0.00603*** | -0.00750*** | -0.00578*** | -0.00666*** |
| % Vacant Units | 0.00479*** | 0.00725*** | 0.00408*** | 0.00385** | 0.00424** | 0.00481*** | 0.00612** |
| **Time Varying** | | | | | | | |
| Logged Population | 0.52554*** | 0.60202*** | 0.65660*** | 0.66843*** | 0.58909*** | 0.64084*** | 0.65436*** |
| % Young People | 0.00482*** | 0.00357* | 0.00210* | 0.00337** | 0.00121 | 0.00260 | 0.00481* |
| Ethnic Heterogeneity | 0.00080 | 0.00064 | 0.00079 | 0.00099 | -0.00105 | 0.00031 | -0.00129 |
| % Low-income | 0.00040 | 0.00316** | -0.00149* | -0.00020 | 0.00242* | 0.00070 | 0.00070 |

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Table .22 – *Continued from previous page*

| | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.00645* | 0.00474 | 0.00866*** | 0.00861** | 0.01521*** | 0.01325*** | 0.01287* |
| % Residential LU | 0.00163 | 0.00344 | 0.00718*** | 0.00781*** | 0.00423* | 0.00525*** | 0.01011*** |
| % Retail LU | 0.01690*** | 0.01215* | 0.01580*** | 0.01079** | 0.01145* | 0.01050** | 0.01169 |
| % Office LU | -0.04379*** | -0.04374** | -0.02614*** | -0.01288 | -0.05639*** | -0.02657** | -0.01776 |
| % School LU | 0.01158 | -0.00987 | -0.01135 | -0.03598*** | -0.03835** | -0.02147* | -0.02799 |
| # of bars | 0.00094 | 0.00174 | 0.00278*** | -0.00029 | 0.00206* | 0.00533*** | 0.00519*** |
| # of grocery stores | -0.00247*** | -0.00253** | -0.00287*** | -0.00255*** | -0.00235*** | -0.00208*** | -0.00289** |
| # of restaurants | -0.00082*** | -0.00016 | -0.00116*** | -0.00079*** | -0.00087*** | -0.00151*** | -0.00099** |
| **Housing** | | | | | | | |
| % Homeowners | 0.00014 | -0.00055 | -0.00609*** | 0.00704*** | 0.00574* | -0.00062 | 0.00694 |
| % Vacant Units | 0.02169*** | 0.01176 | -0.00499 | 0.00970 | 0.02720*** | 0.00596 | 0.02852** |
| **Time Varying** | | | | | | | |
| Logged Population | 0.25479*** | -0.01873 | 0.32640*** | 0.31833*** | 0.42670*** | 0.36238*** | 0.25793 |
| % Young People | 0.00206 | 0.00789 | 0.00718* | 0.01774*** | 0.02235*** | 0.01169* | 0.00215 |
| Ethnic Heterogeneity | -0.00366** | -0.00246 | -0.00403*** | -0.00506*** | -0.00383* | -0.00154 | -0.00546* |
| % Low-income | 0.03350*** | 0.02327*** | 0.02054*** | 0.02864*** | 0.01868*** | 0.02123*** | 0.02841*** |
| Intercept | -15.60611*** | -12.76569*** | -15.67574*** | -17.68215*** | -18.32406*** | -16.90706*** | -17.28563*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: LU = Land Use. Table is unstandardized coefficients.*

Table .23: Summer Motor Theft

| | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|
| | 7am-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | |
| % Industrial LU | 0.00338*** | 0.00390*** | 0.00697*** | 0.01127*** | 0.00392** | 0.00463* |
| % Residential LU | -0.00409*** | -0.00520*** | -0.00523*** | -0.00770*** | -0.00508*** | -0.00661*** |
| % Retail LU | 0.00249** | 0.00485*** | 0.00239* | 0.00731*** | 0.00532*** | 0.00091 |
| % Office LU | -0.00118 | -0.00106 | -0.00234 | 0.00055 | -0.00044 | 0.00060 |
| % School LU | -0.01224*** | -0.00083 | -0.00251 | 0.00024 | 0.00008 | -0.00039 |
| # of bars | 0.09699 | 0.17726** | 0.25819*** | 0.10567 | 0.15723* | 0.24787* |
| # of grocery stores | 0.13896*** | 0.07500* | 0.05884 | 0.05449 | 0.13388** | |
| # of restaurants | 0.07876*** | 0.11495*** | 0.08211*** | 0.16090*** | 0.10388*** | 0.04323 |
| **Housing** | | | | | | |
| % Homeowners | -0.00577*** | -0.00623*** | -0.00631*** | -0.00577*** | -0.00554*** | -0.00662*** |
| % Vacant Units | 0.00405*** | 0.00360*** | 0.00400*** | 0.00309 | 0.00639*** | 0.00431* |
| **Time Varying** | | | | | | |
| Logged Population | 0.54392*** | 0.66094*** | 0.66281*** | 0.60280*** | 0.63179*** | 0.63368*** |
| % Young People | 0.00466*** | 0.00243* | 0.00347** | -0.00237 | 0.00498*** | 0.00628** |
| Ethnic Heterogeneity | 0.00145* | 0.00181** | 0.00028 | 0.00011 | 0.00008 | -0.00134 |
| % Low-income | 0.00080 | -0.00066 | 0.00017 | -0.00066 | -0.00021 | -0.00059 |

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Table .23 – *Continued from previous page*

| | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|
| | 7am-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | |
| **Land Use and Business** | | | | | | |
| % Industrial LU | 0.00807** | 0.00494* | -0.00112 | 0.00662 | 0.01626*** | 0.00785 |
| % Residential LU | 0.00275* | 0.00144 | 0.00367** | 0.00446* | 0.00837*** | 0.00514* |
| % Retail LU | 0.00628 | 0.01086*** | 0.00666* | 0.01163* | 0.01552*** | 0.01464* |
| % Office LU | -0.04374*** | -0.03855*** | -0.03575*** | -0.07967*** | -0.01727 | -0.06368*** |
| % School LU | 0.00740 | -0.01594* | -0.03129*** | -0.04216*** | -0.01617 | -0.00630 |
| # of bars | 0.00208** | 0.00381*** | 0.00104 | 0.00276** | 0.00398*** | 0.00655*** |
| # of grocery stores | -0.00087* | -0.00299*** | -0.00345*** | -0.00301*** | -0.00113* | -0.00215* |
| # of restaurants | -0.00096*** | -0.00122*** | -0.00091*** | -0.00074** | -0.00116*** | -0.00120*** |
| **Housing** | | | | | | |
| % Homeowners | -0.00485** | -0.00693*** | 0.00311 | 0.00275 | -0.00049 | 0.01372*** |
| % Vacant Units | 0.01535** | -0.01114* | 0.00897 | 0.02553** | 0.00018 | 0.03599*** |
| **Time Varying** | | | | | | |
| Logged Population | 0.17271*** | 0.43429*** | 0.39290*** | 0.22572* | 0.20954** | 0.43401*** |
| % Young People | 0.00424 | 0.00238 | 0.00583 | 0.03397*** | 0.00822 | -0.00699 |
| Ethnic Heterogeneity | -0.00477*** | -0.00421*** | -0.00337** | -0.00214 | 0.00113 | 0.00194 |
| % Low-income | 0.02954*** | 0.01985*** | 0.02843*** | 0.02653*** | 0.02023*** | 0.03456*** |
| Intercept | -14.49171*** | -16.47398*** | -17.64578*** | -16.19881*** | -15.35629*** | -19.48898*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .24: Fall Motor Theft

| | 21 | 22 | 23 | 24 | 25 | 26 | 27 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.00360** | -0.00053 | 0.00418*** | 0.00711*** | 0.01161*** | 0.00613*** | 0.00705** |
| % Residential LU | -0.00376*** | -0.00375*** | -0.00485*** | -0.00514*** | -0.00635*** | -0.00559*** | -0.00659*** |
| % Retail LU | 0.00452*** | 0.00406* | 0.00353*** | 0.00282* | 0.00921*** | 0.00573*** | 0.00139 |
| % Office LU | -0.00244 | -0.00237 | -0.00085 | -0.00153 | 0.00471* | 0.00027 | -0.00739 |
| % School LU | -0.00898*** | -0.00153 | 0.00009 | 0.00063 | 0.00644*** | 0.00004 | -0.00160 |
| # of bars | 0.18292** | -0.15044 | 0.14983** | 0.24849*** | 0.25305** | 0.32323*** | 0.26988* |
| # of grocery stores | 0.12099** | 0.26369*** | 0.04177 | 0.10000* | 0.02911 | 0.07292 | 0.10384 |
| # of restaurants | 0.07397*** | 0.11702*** | 0.12689*** | 0.06691*** | 0.12259*** | 0.15015*** | 0.09995** |
| **Housing** | | | | | | | |
| % Homeowners | -0.00579*** | -0.00639*** | -0.00697*** | -0.00608*** | -0.00567*** | -0.00714*** | -0.00740*** |
| % Vacant Units | 0.00544*** | 0.00705*** | 0.00411*** | 0.00532*** | 0.00344* | 0.00278* | 0.00553* |
| **Time Varying** | | | | | | | |
| Logged Population | 0.52857*** | 0.60610*** | 0.64181*** | 0.66815*** | 0.60295*** | 0.61727*** | 0.59151*** |
| % Young People | 0.00372*** | 0.00326 | 0.00150 | 0.00453*** | 0.00004 | 0.00216 | 0.00699** |
| Ethnic Heterogeneity | 0.00267*** | 0.00162 | 0.00204** | 0.00063 | -0.00086 | 0.00082 | 0.00070 |
| % Low-income | 0.00048 | 0.00352*** | -0.00037 | -0.00079 | 0.00192 | -0.00043 | 0.00012 |

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Table .24 – *Continued from previous page*

| | 21 | 22 | 23 | 24 | 25 | 26 | 27 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.00878** | 0.01800*** | 0.00665** | 0.00420 | 0.00841* | 0.00618 | 0.00262 |
| % Residential LU | 0.00202 | 0.00593** | 0.00511*** | 0.00457** | 0.00480* | 0.00559*** | 0.00548* |
| % Retail LU | 0.00663 | 0.01226* | 0.00640* | 0.01293*** | 0.00769 | 0.01150*** | 0.00642 |
| % Office LU | -0.04094*** | -0.03878* | -0.01777* | -0.01866 | -0.05957*** | -0.03428*** | -0.05377** |
| % School LU | 0.00361 | 0.02964 | -0.03429*** | -0.04235*** | -0.03866** | -0.04586*** | -0.06390*** |
| # of bars | 0.00243** | 0.00397** | 0.00430*** | 0.00157 | 0.00421*** | 0.00503*** | 0.00302* |
| # of grocery stores | -0.00119* | -0.00069 | -0.00145*** | -0.00288*** | -0.00199** | -0.00066 | -0.00024 |
| # of restaurants | -0.00105*** | -0.00108*** | -0.00147*** | -0.00085*** | -0.00117*** | -0.00156*** | -0.00098** |
| **Housing** | | | | | | | |
| % Homeowners | -0.00187 | -0.00956** | -0.00413* | 0.00389 | -0.00576* | -0.00172 | 0.00872* |
| % Vacant Units | 0.00948 | 0.00590 | -0.00696 | 0.00164 | 0.00416 | -0.00243 | 0.00262 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.28251*** | -0.03759 | 0.35491*** | 0.36526*** | 0.28435** | 0.43548*** | 0.37709** |
| % Young People | 0.01129* | 0.00054 | 0.01189** | 0.00588 | 0.01486* | 0.01415** | 0.02132* |
| Ethnic Heterogeneity | -0.00554*** | 0.00252 | -0.00129 | -0.00209 | -0.00061 | -0.00269* | -0.00464* |
| % Low-income | 0.03514*** | 0.01919*** | 0.02165*** | 0.03012*** | 0.02277*** | 0.02056*** | 0.02935*** |
| Intercept | -16.00907*** | -12.29498*** | -16.23261*** | -17.68059*** | -16.02122*** | -17.34259*** | -18.23296*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .25: Winter Burglary

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00365*** | 0.00127 | 0.00834*** | 0.00422** | 0.00793*** | 0.00756*** | 0.01066*** |
| % Residential LU | 0.00132*** | -0.00049 | -0.00477*** | -0.00508*** | -0.00362*** | -0.00519*** | -0.00775*** |
| % Retail LU | -0.00355*** | 0.00093 | 0.00919*** | 0.01105*** | 0.00370** | 0.00818*** | 0.00850*** |
| % Office LU | -0.00963*** | -0.01102*** | 0.00546*** | 0.00754*** | 0.00600*** | 0.00768*** | 0.00546 |
| % School LU | -0.01303*** | 0.00668*** | 0.00471*** | 0.00095 | 0.00479** | 0.00532** | 0.00346 |
| # of bars | 0.05051 | -0.03314 | 0.27040*** | 0.28730*** | 0.14332* | 0.03236 | 0.13147 |
| # of grocery stores | 0.11830*** | 0.16058** | 0.18395*** | 0.24650*** | 0.08464 | 0.15679*** | 0.15664* |
| # of restaurants | 0.05553*** | 0.03858* | 0.15166*** | 0.17441*** | 0.10709*** | 0.17600*** | 0.21338*** |
| **Housing** | | | | | | | |
| % Homeowners | -0.00250*** | -0.00143* | -0.00375*** | -0.00372*** | -0.00226*** | -0.00387*** | -0.00638*** |
| % Vacant Units | 0.00920*** | 0.01397*** | 0.00932*** | 0.01070*** | 0.01153*** | 0.01241*** | 0.00314 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.51297*** | 0.57069*** | 0.57072*** | 0.59629*** | 0.63555*** | 0.58593*** | 0.55421*** |
| % Young People | 0.00201*** | -0.00112 | 0.00004 | 0.00137 | -0.00077 | 0.00243 | 0.00552** |
| Ethnic Heterogeneity | 0.00311*** | 0.00075 | 0.00175** | 0.00266*** | 0.00179* | 0.00044 | -0.00117 |
| % Low-income | 0.00062 | 0.00295*** | -0.00012 | -0.00012 | 0.00186* | 0.00122 | 0.00042 |

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Table .25 – *Continued from previous page*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00146 | -0.00085 | -0.00315 | -0.00354 | -0.00691* | -0.00641 | 0.00210 |
| % Residential LU | 0.00940*** | 0.00769*** | 0.01070*** | 0.01015*** | 0.00991*** | 0.00834*** | 0.01250*** |
| % Retail LU | 0.01380*** | 0.00702 | 0.01758*** | 0.01608*** | 0.01348*** | 0.01030** | 0.02679*** |
| % Office LU | 0.00887 | -0.00253 | -0.00257 | -0.01730* | 0.00274 | -0.00541 | -0.02705 |
| % School LU | 0.02474*** | 0.00802 | -0.00394 | -0.00775 | 0.00890 | -0.00591 | -0.00775 |
| # of bars | 0.00240*** | -0.00007 | 0.00438*** | 0.00447*** | 0.00199* | 0.00545*** | 0.00463*** |
| # of grocery stores | -0.00259*** | -0.00324*** | -0.00203*** | -0.00211*** | -0.00315*** | -0.00193** | -0.00239* |
| # of restaurants | -0.00044*** | -0.00019 | -0.00070*** | -0.00099*** | -0.00068*** | -0.00066** | -0.00027 |
| **Housing** | | | | | | | |
| % Homeowners | -0.00575*** | -0.00932*** | -0.00176 | -0.00070 | -0.00258 | -0.00000 | 0.00156 |
| % Vacant Units | 0.02626*** | 0.03320*** | 0.02404*** | 0.01939*** | 0.02656*** | 0.01731** | 0.02545** |
| **Time Varying** | | | | | | | |
| Logged Population | -0.24758*** | -0.25666*** | -0.23573*** | -0.19383** | -0.16137* | -0.26908*** | -0.37553** |
| % Young People | 0.00239 | 0.00616 | 0.00229 | 0.01046*** | 0.00861* | 0.00625 | 0.02036*** |
| Ethnic Heterogeneity | 0.00208** | -0.00370* | -0.00047 | -0.00237* | -0.00225 | -0.00145 | -0.00379 |
| % Low-income | 0.02438*** | 0.00980*** | 0.01718*** | 0.02164*** | 0.02530*** | 0.01751*** | 0.01301** |
| Intercept | -9.72167*** | -9.12400*** | -10.16576*** | -11.15225*** | -11.57675*** | -9.72973*** | -9.43682*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .26: Spring Burglary

| | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00337*** | 0.00117 | 0.00551*** | 0.00444*** | 0.00775*** | 0.00761*** | 0.00659** |
| % Residential LU | 0.00185*** | 0.00037 | -0.00526*** | -0.00509*** | -0.00320*** | -0.00400*** | -0.00698*** |
| % Retail LU | -0.00457*** | -0.00059 | 0.00728*** | 0.00996*** | 0.00402*** | 0.00903*** | 0.01023*** |
| % Office LU | -0.00512*** | -0.00372 | 0.00504*** | 0.00456** | 0.00393* | 0.00974*** | 0.00716** |
| % School LU | -0.01286*** | 0.00906*** | 0.00349** | 0.00006 | 0.00583*** | 0.00633*** | -0.00052 |
| # of bars | 0.03069 | 0.13555 | 0.07218 | 0.13830* | 0.10299 | 0.09653 | 0.06142 |
| # of grocery stores | 0.10120*** | 0.11877* | 0.18502*** | 0.19698*** | 0.06645 | 0.11687** | 0.28774*** |
| # of restaurants | 0.07150*** | 0.08076*** | 0.16469*** | 0.20220*** | 0.11597*** | 0.14808*** | 0.21770*** |
| **Housing** | | | | | | | |
| % Homeowners | -0.00244*** | -0.00231*** | -0.00304*** | -0.00475*** | -0.00300*** | -0.00481*** | -0.00446*** |
| % Vacant Units | 0.00932*** | 0.01140*** | 0.01100*** | 0.00776*** | 0.01117*** | 0.01025*** | 0.00775*** |
| **Time Varying** | | | | | | | |
| Logged Population | 0.51228*** | 0.57311*** | 0.56572*** | 0.56443*** | 0.63667*** | 0.57721*** | 0.56096*** |
| % Young People | 0.00285*** | 0.00014 | 0.00010 | 0.00166 | 0.00095 | -0.00035 | 0.00418* |
| Ethnic Heterogeneity | 0.00317*** | 0.00053 | 0.00106 | 0.00214*** | 0.00223** | 0.00011 | -0.00017 |
| % Low-income | 0.00037 | 0.00392*** | 0.00113 | -0.00117 | 0.00102 | -0.00028 | 0.00183 |

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Table .26 – *Continued from previous page*

| | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00034 | -0.00292 | 0.00069 | -0.00376 | -0.00107 | -0.00161 | 0.00128 |
| % Residential LU | 0.00968*** | 0.00927*** | 0.01171*** | 0.01071*** | 0.01112*** | 0.01316*** | 0.00861*** |
| % Retail LU | 0.01517*** | 0.01694*** | 0.01533*** | 0.01930*** | 0.01329*** | 0.01694*** | 0.01851*** |
| % Office LU | -0.00317 | -0.00284 | 0.00412 | -0.00184 | -0.01361 | 0.00724 | -0.02233 |
| % School LU | 0.02694*** | 0.00314 | -0.01654* | -0.00129 | -0.00115 | -0.00359 | -0.01617 |
| # of bars | 0.00374*** | 0.00345*** | 0.00382*** | 0.00418*** | 0.00425*** | 0.00589*** | 0.00608*** |
| # of grocery stores | -0.00138*** | -0.00174** | -0.00226*** | -0.00258*** | -0.00157** | -0.00149* | -0.00178 |
| # of restaurants | -0.00092*** | -0.00089*** | -0.00054*** | -0.00081*** | -0.00121*** | -0.00091*** | -0.00060 |
| **Housing** | | | | | | | |
| % Homeowners | -0.00596*** | -0.00270 | 0.00107 | 0.00210 | 0.00051 | 0.00158 | -0.00120 |
| % Vacant Units | 0.02875*** | 0.04559*** | 0.02446*** | 0.02914*** | 0.03302*** | 0.02665*** | 0.00497 |
| **Time Varying** | | | | | | | |
| Logged Population | -0.25456*** | -0.28854*** | -0.24486*** | -0.19248*** | -0.19755** | -0.33836*** | -0.18728 |
| % Young People | 0.00102 | 0.01540** | 0.01204*** | 0.01036*** | 0.00711* | 0.01075** | 0.01043 |
| Ethnic Heterogeneity | -0.00038 | -0.00210 | -0.00187* | -0.00100 | -0.00320** | -0.00096 | -0.00170 |
| % Low-income | 0.02384*** | 0.01318*** | 0.01859*** | 0.02461*** | 0.02560*** | 0.02064*** | 0.02121*** |
| Intercept | -9.38869*** | -9.70388*** | -10.22029*** | -11.14436*** | -11.20101*** | -9.17794*** | -11.22144*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: LU = Land Use. Table is unstandardized coefficients.*

Table .27: Summer Burglary

| | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|
| | 7am-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | |
| % Industrial LU | -0.00431*** | 0.00696*** | 0.00564*** | 0.00477*** | 0.00850*** | 0.00284 |
| % Residential LU | 0.00122*** | -0.00445*** | -0.00497*** | -0.00295*** | -0.00453*** | -0.00699*** |
| % Retail LU | -0.00343*** | 0.00763*** | 0.00913*** | 0.00524*** | 0.00595*** | 0.01047*** |
| % Office LU | -0.00687*** | 0.00522*** | 0.00339* | 0.00697*** | 0.00664*** | 0.00565* |
| % School LU | -0.01147*** | 0.00296* | 0.00211 | 0.00467** | 0.00637*** | 0.00221 |
| # of bars | 0.05591 | 0.06037 | 0.17493*** | 0.04706 | 0.09543 | 0.29876*** |
| # of grocery stores | 0.10749*** | 0.14817*** | 0.21171*** | 0.07732* | 0.17750*** | |
| # of restaurants | 0.05454*** | 0.15627*** | 0.18891*** | 0.11049*** | 0.14323*** | 0.11467*** |
| **Housing** | | | | | | |
| % Homeowners | -0.00267*** | -0.00315*** | -0.00454*** | -0.00337*** | -0.00427*** | -0.00320*** |
| % Vacant Units | 0.01018*** | 0.01092*** | 0.00980*** | 0.01200*** | 0.01038*** | 0.00758*** |
| **Time Varying** | | | | | | |
| Logged Population | 0.50230*** | 0.57065*** | 0.57374*** | 0.61276*** | 0.56718*** | 0.57653*** |
| % Young People | 0.00118** | 0.00000 | 0.00195* | -0.00218 | 0.00028 | 0.00149 |
| Ethnic Heterogeneity | 0.00301*** | 0.00127* | 0.00177** | 0.00372*** | 0.00147* | 0.00188 |
| % Low-income | 0.00133*** | 0.00238*** | 0.00053 | 0.00126 | 0.00114 | 0.00382** |

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Table .27 – *Continued from previous page*

| | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|
| | 7am-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | |
| **Land Use and Business** | | | | | | |
| % Industrial LU | 0.00231 | 0.00033 | 0.00337 | -0.00149 | 0.00087 | 0.01410** |
| % Residential LU | 0.01066*** | 0.01024*** | 0.01402*** | 0.01269*** | 0.01276*** | 0.01739*** |
| % Retail LU | 0.01466*** | 0.01170*** | 0.02130*** | 0.01250*** | 0.01779*** | 0.03111*** |
| % Office LU | -0.00880 | -0.00701 | -0.01301 | -0.00382 | -0.01942* | -0.02361 |
| % School LU | 0.03343*** | 0.01998** | -0.00653 | 0.02014* | -0.00256 | 0.01246 |
| # of bars | 0.00325*** | 0.00512*** | 0.00540*** | 0.00394*** | 0.00415*** | 0.00537*** |
| # of grocery stores | -0.00217*** | -0.00232*** | -0.00264*** | -0.00224*** | -0.00168** | -0.00283** |
| # of restaurants | -0.00063*** | -0.00075*** | -0.00097*** | -0.00089*** | -0.00047** | -0.00052 |
| **Housing** | | | | | | |
| % Homeowners | -0.00888*** | -0.00219 | -0.00125 | -0.00199 | -0.00077 | 0.00552 |
| % Vacant Units | 0.03709*** | 0.02628*** | 0.03068*** | 0.02979*** | 0.02521*** | 0.03533*** |
| **Time Varying** | | | | | | |
| Logged Population | -0.30129*** | -0.32106*** | -0.26765*** | -0.23460*** | -0.39934*** | -0.33592** |
| % Young People | 0.00632** | 0.00310 | 0.00684** | 0.00684* | 0.01128*** | 0.02278*** |
| Ethnic Heterogeneity | -0.00219*** | -0.00090 | -0.00227** | -0.00534*** | -0.00340** | -0.00182 |
| % Low-income | 0.01764*** | 0.01937*** | 0.02118*** | 0.02318*** | 0.01962*** | 0.01877*** |
| Intercept | -8.56890*** | -8.91390*** | -9.92494*** | -10.28812*** | -8.06532*** | -10.62655*** |

$*p < .05; **p < .01; ***p < .001$

*Note: LU = Land Use. Table is unstandardized coefficients.*

Table .28: Fall Burglary

| | 21 | 22 | 23 | 24 | 25 | 26 | 27 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00429*** | -0.00191 | 0.00537*** | 0.00574*** | 0.00984*** | 0.00861*** | 0.01021*** |
| % Residential LU | 0.00196*** | -0.00083 | -0.00496*** | -0.00448*** | -0.00284*** | -0.00403*** | -0.00742*** |
| % Retail LU | -0.00331*** | 0.00062 | 0.00677*** | 0.01085*** | 0.00481*** | 0.00987*** | 0.01138*** |
| % Office LU | -0.00616*** | -0.00304 | 0.00596*** | 0.00527** | 0.00490** | 0.01070*** | 0.00693* |
| % School LU | -0.01211*** | 0.00559*** | 0.00272* | 0.00198 | 0.00417** | 0.00878*** | -0.00003 |
| # of bars | 0.08201 | -0.11124 | 0.03135 | 0.18274** | 0.11990 | 0.05303 | 0.15602 |
| # of grocery stores | 0.09057*** | 0.15720** | 0.19473*** | 0.24530*** | 0.12671** | 0.09856* | 0.30664*** |
| # of restaurants | 0.05295*** | 0.06199** | 0.16607*** | 0.19555*** | 0.11362*** | 0.13442*** | 0.19888*** |
| **Housing** | | | | | | | |
| % Homeowners | -0.00204*** | -0.00163** | -0.00354*** | -0.00276*** | -0.00321*** | -0.00495*** | -0.00586*** |
| % Vacant Units | 0.00915*** | 0.01299*** | 0.01080*** | 0.00967*** | 0.01186*** | 0.01106*** | 0.00652*** |
| **Time Varying** | | | | | | | |
| Logged Population | 0.50690*** | 0.56940*** | 0.56453*** | 0.57069*** | 0.61156*** | 0.56487*** | 0.51715*** |
| % Young People | 0.00176*** | 0.00058 | -0.00105 | 0.00501*** | -0.00040 | 0.00127 | 0.00699*** |
| Ethnic Heterogeneity | 0.00317*** | 0.00066 | 0.00189** | 0.00174** | 0.00287*** | 0.00158* | 0.00189 |
| % Low-income | 0.00053 | 0.00442*** | 0.00144* | 0.00211** | 0.00177* | 0.00046 | 0.00137 |

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Table .28 – *Continued from previous page*

| | 21 | 22 | 23 | 24 | 25 | 26 | 27 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.00296 | 0.00168 | 0.00081 | 0.00021 | -0.00769** | -0.00803* | 0.00350 |
| % Residential LU | 0.01241*** | 0.00762*** | 0.01350*** | 0.01225*** | 0.01042*** | 0.01132*** | 0.01231*** |
| % Retail LU | 0.01858*** | 0.01846*** | 0.02114*** | 0.02132*** | 0.00880** | 0.01443*** | 0.01454** |
| % Office LU | -0.00088 | 0.00465 | -0.00849 | -0.00526 | 0.00144 | -0.00613 | -0.00338 |
| % School LU | 0.03180*** | 0.02748** | -0.00451 | -0.01572* | 0.00647 | -0.00902 | -0.04063** |
| # of bars | 0.00221*** | 0.00316** | 0.00449*** | 0.00381*** | 0.00335*** | 0.00434*** | 0.00490*** |
| # of grocery stores | -0.00270*** | -0.00129* | -0.00186*** | -0.00239*** | -0.00226*** | -0.00235*** | -0.00120 |
| # of restaurants | -0.00063*** | -0.00116*** | -0.00064*** | -0.00116*** | -0.00098*** | -0.00050** | -0.00089** |
| **Housing** | | | | | | | |
| % Homeowners | -0.00811*** | -0.00447* | -0.00226 | -0.00223 | -0.00012 | -0.00038 | 0.00332 |
| % Vacant Units | 0.03424*** | 0.03406*** | 0.02073*** | 0.02464*** | 0.02911*** | 0.02554*** | 0.02848*** |
| **Time Varying** | | | | | | | |
| Logged Population | -0.29960*** | -0.26140*** | -0.41256*** | -0.15442** | -0.19809** | -0.34643*** | -0.14467 |
| % Young People | 0.00363 | 0.00888 | 0.00985*** | 0.01035*** | 0.01026** | 0.00933** | 0.02103*** |
| Ethnic Heterogeneity | -0.00096 | -0.00160 | -0.00171* | -0.00249** | -0.00447*** | -0.00453*** | -0.00389* |
| % Low-income | 0.02236*** | 0.01098*** | 0.02163*** | 0.02018*** | 0.02504*** | 0.02194*** | 0.01382*** |
| Intercept | -8.65848*** | -9.34757*** | -8.03238*** | -11.26904*** | -10.83072*** | -8.58699*** | -11.82722*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: LU = Land Use. Table is unstandardized coefficients.*

# Appendix E: Models for each City

See next page.

Table .29: Violent Crime Models: Atlanta

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.00208 | 0.00123 | -0.00158 | -0.00123 | 0.00113 | -0.00105 | | | |
| % Residential LU | -0.00548*** | -0.00287*** | -0.00210*** | -0.00809*** | -0.00565*** | -0.00476*** | | | |
| % Retail LU | 0.01564*** | 0.00962*** | 0.00767*** | 0.01520*** | 0.01033*** | 0.00800*** | | | |
| % Office LU | -0.00254 | -0.00549 | -0.01240** | 0.00905* | 0.00246 | -0.00298 | | | |
| % School LU | -0.00246 | -0.00302 | -0.00618** | -0.00269 | -0.00363 | -0.00577** | | | |
| # of bars | 0.59309*** | 0.37381*** | 0.35786*** | 0.27206 | 0.00631 | -0.02413 | | | |
| # of grocery stores | 0.43499*** | 0.30650*** | 0.30764*** | 0.85507*** | 0.66287*** | 0.65027*** | | | |
| # of restaurants | 0.29791*** | 0.21103*** | 0.20278*** | 0.42797*** | 0.31871*** | 0.30816*** | | | |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00976*** | -0.00896*** | -0.00993*** | -0.00683*** | -0.00743*** | -0.00766*** | | | |
| % Vacant Units | 0.01270*** | 0.01224*** | 0.01106*** | 0.00768*** | 0.00685*** | 0.00622*** | | | |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.56773*** | 0.58290*** | 0.52785*** | 0.53319*** | 0.50417*** | 0.47668*** | | | |
| % Young People | -0.00341 | -0.00494*** | -0.00259* | 0.00027 | 0.00089 | 0.00212 | | | |
| Ethnic Heterogeneity | -0.00632*** | -0.00802*** | -0.00815*** | -0.00213 | -0.00225* | -0.00238* | | | |
| % Low-income | 0.00566*** | 0.00458*** | 0.00537*** | 0.00260 | 0.00198* | 0.00380*** | | | |

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Table .29 – *Continued from previous page*

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | -0.04846* | -0.04419*** | -0.04842*** | -0.01386 | -0.00563 | -0.01346 | | | |
| % Residential LU | -0.00442 | -0.00657*** | -0.00733*** | -0.00039 | -0.00241 | -0.00313 | | | |
| % Retail LU | -0.00447 | -0.01708 | -0.02812* | -0.01027 | -0.00137 | -0.01951 | | | |
| % Office LU | -0.01423 | -0.01515 | -0.02866* | -0.02183 | 0.00457 | -0.01747 | | | |
| % School LU | -0.06817* | -0.07669*** | -0.04418* | -0.01903 | -0.04199* | -0.01537 | | | |
| # of bars | 0.00567 | -0.00389 | -0.00407 | 0.00841 | 0.00409 | 0.00556* | | | |
| # of grocery stores | 0.00796** | 0.00534** | 0.00652*** | 0.00451 | 0.00532** | 0.00764*** | | | |
| # of restaurants | -0.00080 | 0.00040 | 0.00068 | 0.00130 | 0.00112* | 0.00116** | | | |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.01118 | -0.01241** | -0.02069*** | -0.02826*** | -0.02515*** | -0.03071*** | | | |
| % Vacant Units | 0.01950 | 0.02009** | 0.03479*** | 0.00133 | -0.01326 | -0.00016 | | | |
| **Time Varying** | | | | | | | | | |
| Logged Population | -0.48804** | -0.27854* | -0.49134*** | -0.42390* | -0.23424* | -0.61401*** | | | |
| % Young People | -0.00292 | -0.01134 | -0.02388*** | -0.01750 | -0.01861** | -0.01896*** | | | |
| Ethnic Heterogeneity | 0.01166*** | 0.01408*** | 0.01725*** | 0.01149*** | 0.00806*** | 0.01193*** | | | |
| % Low-income | 0.03674*** | 0.03214*** | 0.02137*** | 0.03605*** | 0.03035*** | 0.02042*** | | | |
| Intercept | 2.16126 | -10.30893*** | -7.02277*** | 2.39429 | -9.58631*** | -5.11025*** | | | |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. The 'yearly' models also include city fixed effects. These are not included in the table for parsimony. No homicide data for Atlanta.*

Table .30: Property Crime Models: Atlanta

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.01329*** | 0.01024*** | 0.00726*** | 0.00592 | 0.00634*** | 0.00317 | 0.01771*** | 0.01069*** | 0.00550*** |
| % Residential LU | -0.00812*** | -0.00636*** | -0.00495*** | -0.00625*** | -0.00368*** | -0.00311*** | -0.00251*** | -0.00176*** | -0.00078** |
| % Retail LU | 0.01794*** | 0.01702*** | 0.01602*** | 0.01592*** | 0.01467*** | 0.01196*** | 0.01301*** | 0.00727*** | 0.00395** |
| % Office LU | 0.01226*** | 0.00491*** | -0.00054 | 0.00724 | 0.00111 | -0.00618* | 0.00784* | 0.00087 | -0.00833*** |
| % School LU | 0.00862** | 0.00605*** | 0.00294** | -0.00318 | -0.00262 | -0.00527** | -0.00473 | -0.00480*** | -0.00784*** |
| # of bars | 0.51476*** | 0.29856*** | 0.26441*** | 0.32857* | 0.16506** | 0.12813* | 0.27226** | 0.13287** | 0.09619* |
| # of grocery stores | 0.64692*** | 0.61692*** | 0.58590*** | 0.42041*** | 0.39100*** | 0.38892*** | 0.22407*** | 0.23382*** | 0.23260*** |
| # of restaurants | 0.46506*** | 0.40477*** | 0.39140*** | 0.25260*** | 0.19355*** | 0.18319*** | 0.18067*** | 0.17906*** | 0.19512*** |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00346*** | -0.00392*** | -0.00405*** | -0.00714*** | -0.00764*** | -0.00794*** | -0.00433*** | -0.00352*** | -0.00554*** |
| % Vacant Units | 0.00610*** | 0.00530*** | 0.00467*** | 0.00253 | 0.00177 | 0.00062 | 0.01296*** | 0.01280*** | 0.01095*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.53241*** | 0.48010*** | 0.46701*** | 0.57051*** | 0.59480*** | 0.55175*** | 0.60814*** | 0.62298*** | 0.48659*** |
| % Young People | -0.00162 | -0.00139* | -0.00057 | -0.00022 | -0.00011 | 0.00261* | -0.00062 | 0.00036 | 0.00185** |
| Ethnic Heterogeneity | -0.00105 | 0.00078 | 0.00100* | -0.00229 | -0.00205* | -0.00237* | 0.00265* | 0.00190*** | 0.00063 |
| % Low-income | -0.00265* | -0.00320*** | -0.00032 | -0.00118 | 0.00047 | 0.00226** | 0.00175 | 0.00207*** | 0.00293*** |

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Table .30 – *Continued from previous page*

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | -0.01879 | -0.00050 | 0.00369 | -0.00269 | 0.00560 | 0.00252 | -0.02237 | -0.00751 | -0.02069** |
| % Residential LU | -0.00170 | -0.00295*** | -0.00598*** | -0.00543* | -0.00730*** | -0.00851*** | -0.00013 | -0.00143 | -0.00102 |
| % Retail LU | 0.00346 | 0.00147 | -0.01128 | 0.03146 | 0.01822 | 0.00244 | -0.01882 | -0.01634* | -0.02725*** |
| % Office LU | 0.00144 | 0.00836 | -0.00544 | -0.00603 | 0.00372 | -0.01852 | -0.00554 | -0.01025 | -0.03083*** |
| % School LU | 0.00397 | -0.03303** | 0.00904 | -0.04277 | -0.04095* | 0.00677 | -0.00699 | -0.01600 | -0.00230 |
| # of bars | 0.01742*** | 0.01546*** | 0.01105*** | 0.01295** | 0.01228*** | 0.01027*** | -0.00957** | -0.01086*** | -0.00859*** |
| # of grocery stores | -0.00160 | -0.00085 | -0.00067 | -0.00133 | 0.00045 | 0.00179 | 0.00625** | 0.00594*** | 0.00776*** |
| # of restaurants | 0.00235*** | 0.00210*** | 0.00261*** | 0.00063 | -0.00007 | 0.00062 | -0.00120* | -0.00125*** | -0.00107*** |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.01308** | -0.01514*** | -0.02064*** | -0.01150 | -0.00672 | -0.01719*** | -0.00998* | -0.00791*** | -0.01213*** |
| % Vacant Units | -0.01698* | -0.02660*** | -0.01144*** | -0.04809*** | -0.05585*** | -0.03243*** | -0.00056 | -0.00061 | 0.00961** |
| **Time Varying** | | | | | | | | | |
| Logged Population | -0.59214*** | -0.51027*** | -0.41042*** | -0.05269 | 0.02966 | -0.22380** | -0.14562 | -0.03079 | -0.44741*** |
| % Young People | 0.01213 | 0.01475*** | -0.00010 | 0.01668 | 0.01779** | 0.00075 | -0.01119 | -0.01009** | -0.00741* |
| Ethnic Heterogeneity | 0.00199 | -0.00232* | 0.00069 | -0.00169 | -0.00460* | -0.00151 | 0.00369 | 0.00236* | 0.00653*** |
| % Low-income | 0.02529*** | 0.02273*** | 0.00761*** | 0.04392*** | 0.03588*** | 0.01925*** | 0.02036*** | 0.01615*** | 0.01047*** |
| Intercept | 5.83302*** | -4.56685*** | -4.62975*** | -1.32239 | -12.65877*** | -8.66326*** | 0.50572 | -10.48578*** | -5.18729*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. The 'yearly' models also include city fixed effects. These are not included in the table for parsimony.*

Table .31: Violent Crime Models: Chicago

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | -0.00417*** | -0.00395*** | -0.00536*** | -0.00716*** | -0.00671*** | -0.00765*** | -0.00492 | -0.00250 | -0.00226 |
| % Residential LU | -0.00922*** | -0.00813*** | -0.00707*** | -0.01406*** | -0.01328*** | -0.01255*** | -0.00644*** | -0.00592*** | -0.00502*** |
| % Retail LU | 0.01984*** | 0.01794*** | 0.01576*** | 0.01356*** | 0.01333*** | 0.01233*** | 0.02328* | 0.02022* | 0.01877* |
| % Office LU | -0.06350 | -0.14126 | -0.17543 | -0.19008 | -0.21968 | -0.28588 | 0.00000 | 0.00000 | 0.00000 |
| % School LU | 0.01433*** | 0.01026*** | 0.00391*** | -0.00024 | -0.00071 | -0.00311*** | -0.00211 | -0.00195 | -0.00563 |
| # of bars | 0.14937*** | 0.10351*** | 0.10566*** | 0.11451* | 0.08187** | 0.08699** | -0.10899 | -0.08526 | -0.08334 |
| # of grocery stores | 0.22226*** | 0.17847*** | 0.18658*** | 0.36764*** | 0.32280*** | 0.32690*** | 0.15686 | 0.14668 | 0.15130 |
| # of restaurants | 0.20143*** | 0.15036*** | 0.14126*** | 0.22409*** | 0.16699*** | 0.16433*** | 0.04154 | 0.06141 | 0.06416 |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00944*** | -0.00947*** | -0.00968*** | -0.00420*** | -0.00420*** | -0.00427*** | -0.00618*** | -0.00638*** | -0.00678*** |
| % Vacant Units | 0.00673*** | 0.00675*** | 0.00689*** | 0.00560*** | 0.00542*** | 0.00525*** | 0.00934*** | 0.00921*** | 0.00809*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.55303*** | 0.58558*** | 0.55795*** | 0.41588*** | 0.40775*** | 0.37452*** | 0.53543*** | 0.52204*** | 0.48095*** |
| % Young People | -0.00301*** | -0.00428*** | -0.00025 | -0.00272*** | -0.00267*** | 0.00030 | 0.00435 | 0.00365 | 0.00425 |
| Ethnic Heterogeneity | -0.00193*** | -0.00320*** | -0.00290*** | -0.00252*** | -0.00343*** | -0.00256*** | -0.00822*** | -0.00846*** | -0.00816*** |
| % Low-income | 0.00539*** | 0.00508*** | 0.00494*** | 0.00185*** | 0.00194*** | 0.00274*** | 0.00462* | 0.00541** | 0.00428* |

*Continued on next page*

Table .31 – *Continued from previous page*

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.02471*** | 0.02365*** | 0.04049*** | 0.03107*** | 0.03675*** | 0.05667*** | 0.05957** | 0.05398** | 0.06104*** |
| % Residential LU | 0.02684*** | 0.02742*** | 0.01887*** | 0.05205*** | 0.05121*** | 0.04065*** | 0.02506** | 0.02494*** | 0.02686*** |
| % Retail LU | -0.00913 | -0.03497* | -0.05181*** | 0.02260 | 0.01582 | -0.00460 | -0.21285 | -0.17514 | -0.13808 |
| % Office LU | 0.01531 | 0.08744* | 0.15144*** | 0.07136 | 0.11702* | 0.22067*** | 0.01808 | 0.05987 | 0.14514 |
| % School LU | 0.00550 | -0.00586 | 0.03048*** | -0.00429 | -0.01728* | 0.01664* | 0.10310* | 0.11098** | 0.11023** |
| # of bars | -0.00387*** | -0.00337*** | -0.00191*** | -0.00962*** | -0.00944*** | -0.00806*** | -0.00619* | -0.00646* | -0.00814** |
| # of grocery stores | 0.00012 | 0.00014 | -0.00025 | -0.00159*** | -0.00110*** | -0.00163*** | 0.00244 | 0.00247 | 0.00424** |
| # of restaurants | 0.00058*** | 0.00053*** | -0.00009 | 0.00194*** | 0.00174*** | 0.00108*** | -0.00046 | -0.00027 | -0.00060 |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00277 | -0.00793*** | -0.00768*** | -0.01767*** | -0.02418*** | -0.02352*** | 0.00743 | 0.00726 | -0.00111 |
| % Vacant Units | 0.03794*** | 0.03138*** | 0.06129*** | -0.00072 | 0.00067 | 0.04067*** | 0.05856* | 0.05011* | 0.06293*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | -0.78693*** | -0.85072*** | -0.30082*** | -0.80974*** | -0.80699*** | -0.10051** | 0.10498 | -0.00462 | -0.15997 |
| % Young People | 0.04002*** | 0.03304*** | -0.00244 | 0.12251*** | 0.10553*** | 0.07092*** | 0.02058 | 0.02155 | 0.03588 |
| Ethnic Heterogeneity | 0.00080 | 0.00159*** | 0.00140** | -0.00817*** | -0.00748*** | -0.00874*** | -0.00120 | -0.00020 | -0.00140 |
| % Low-income | 0.02258*** | 0.01751*** | 0.00005 | 0.04181*** | 0.02792*** | 0.00507** | 0.02949 | 0.03034* | 0.01050 |
| Intercept | 4.88144*** | -4.30789*** | -9.40249*** | 3.26999*** | -6.34338*** | -12.99245*** | -10.70672* | -20.66393*** | -17.88453*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. The 'yearly' models also include city fixed effects. These are not included in the table for parsimony.*

Table .32: Property Crime Models: Chicago

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | -0.00079 | -0.00107* | -0.00235*** | 0.00312*** | 0.00337*** | 0.00258*** | 0.00172 | 0.00135 | 0.00027 |
| % Residential LU | -0.01364*** | -0.01240*** | -0.01144*** | -0.00693*** | -0.00657*** | -0.00531*** | -0.00170*** | -0.00160*** | 0.00042* |
| % Retail LU | 0.03818*** | 0.03728*** | 0.03503*** | 0.01036*** | 0.01021*** | 0.00771*** | 0.00754** | 0.00929*** | 0.00677*** |
| % Office LU | -0.00219 | -0.00346 | -0.01135 | -0.04615 | -0.04706 | -0.06468 | -0.03429 | -0.05102 | -0.06822 |
| % School LU | 0.00541*** | 0.00418*** | 0.00040 | -0.00112 | -0.00156* | -0.00453*** | -0.00181* | -0.00228*** | -0.00537*** |
| # of bars | 0.09792*** | 0.13285*** | 0.13421*** | 0.08488* | 0.06966* | 0.06924* | 0.03949 | 0.03707 | 0.05090* |
| # of grocery stores | 0.28120*** | 0.24032*** | 0.24161*** | 0.05268* | 0.04996* | 0.06403** | 0.07003** | 0.07471*** | 0.11105*** |
| # of restaurants | 0.21608*** | 0.18529*** | 0.17541*** | 0.07353*** | 0.06026*** | 0.06013*** | 0.12097*** | 0.09751*** | 0.10432*** |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00274*** | -0.00259*** | -0.00215*** | -0.00426*** | -0.00412*** | -0.00431*** | -0.00243*** | -0.00263*** | -0.00353*** |
| % Vacant Units | 0.00317*** | 0.00355*** | 0.00378*** | 0.00156** | 0.00148*** | 0.00104* | 0.01014*** | 0.01041*** | 0.00913*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.46585*** | 0.46619*** | 0.45491*** | 0.47860*** | 0.50047*** | 0.43783*** | 0.56410*** | 0.57987*** | 0.44103*** |
| % Young People | -0.00226*** | -0.00268*** | 0.00071** | -0.00084 | -0.00088 | 0.00120** | 0.00200*** | 0.00240*** | 0.00328*** |
| Ethnic Heterogeneity | -0.00037 | -0.00072*** | 0.00029 | -0.00090* | -0.00107*** | -0.00120*** | 0.00179*** | 0.00127*** | -0.00035 |
| % Low-income | -0.00038 | 0.00008 | 0.00145*** | -0.00045 | -0.00042 | 0.00003 | -0.00102** | -0.00067* | 0.00050* |

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Table .32 – *Continued from previous page*

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | -0.00637* | -0.01266*** | 0.00028 | 0.05318*** | 0.04547*** | 0.04808*** | 0.01069*** | 0.01035*** | 0.02516*** |
| % Residential LU | 0.02489*** | 0.02012*** | 0.01416*** | 0.01728*** | 0.01635*** | 0.01670*** | 0.03661*** | 0.03675*** | 0.02825*** |
| % Retail LU | -0.01526 | -0.03020*** | -0.03537*** | 0.10345*** | 0.09871*** | 0.10330*** | -0.06053*** | -0.06876*** | -0.04924*** |
| % Office LU | 0.23340*** | 0.17693*** | 0.21670*** | 0.19264*** | 0.21337*** | 0.23530*** | -0.04017 | 0.02861 | 0.14076*** |
| % School LU | -0.02828*** | -0.03557*** | -0.00711* | 0.03688*** | 0.03272*** | 0.02858*** | 0.01606* | 0.01081* | 0.03055*** |
| # of bars | -0.00306*** | -0.00160*** | -0.00055** | -0.00131** | -0.00080* | -0.00123*** | 0.00121** | 0.00160*** | 0.00079** |
| # of grocery stores | -0.00195*** | -0.00181*** | -0.00210*** | -0.00275*** | -0.00249*** | -0.00139*** | -0.00416*** | -0.00430*** | -0.00377*** |
| # of restaurants | 0.00141*** | 0.00129*** | 0.00089*** | -0.00008 | -0.00021* | -0.00058*** | 0.00070*** | 0.00055*** | 0.00002 |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.01579*** | -0.01476*** | -0.01330*** | -0.00479*** | -0.00522*** | -0.01180*** | 0.00091 | -0.00235** | -0.00877*** |
| % Vacant Units | 0.04023*** | 0.04757*** | 0.06692*** | 0.00763 | 0.01033** | 0.01382*** | 0.00260 | 0.00457 | 0.03772*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | -0.83613*** | -0.77748*** | -0.35737*** | 0.56610*** | 0.51680*** | 0.45417*** | -0.57007*** | -0.56548*** | -0.19162*** |
| % Young People | 0.06430*** | 0.04691*** | 0.02617*** | 0.04035*** | 0.03553*** | 0.03808*** | 0.05211*** | 0.04385*** | 0.03107*** |
| Ethnic Heterogeneity | -0.00155*** | -0.00090** | -0.00205*** | -0.00723*** | -0.00690*** | -0.00747*** | -0.00244*** | -0.00195*** | -0.00197*** |
| % Low-income | 0.00229 | -0.00105 | -0.01337*** | 0.02886*** | 0.02612*** | 0.01303*** | 0.05638*** | 0.05079*** | 0.01974*** |
| Intercept | 8.12754*** | -2.30253*** | -6.44394*** | -10.16354*** | -19.67188*** | -17.84084*** | 0.50265 | -9.03643*** | -11.28246*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. The 'yearly' models also include city fixed effects. These are not included in the table for parsimony.*

Table .33: Violent Crime Models: Cincinnati

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | | | | -0.00188 | -0.00219 | -0.00374* | 0.00981 | 0.00885 | 0.00461 |
| % Residential LU | | | | -0.00692*** | -0.00591*** | -0.00599*** | -0.00541 | -0.00323 | -0.00318 |
| % Retail LU | | | | 0.01933*** | 0.01504*** | 0.01370*** | -0.00075 | 0.00163 | -0.00102 |
| % Office LU | | | | 0.01303** | 0.01072*** | 0.00737*** | -0.02891 | -0.02423 | -0.02951 |
| % School LU | | | | 0.00713** | 0.00610*** | 0.00420** | 0.01689* | 0.01292 | 0.00772 |
| # of bars | | | | 0.15811 | 0.22375** | 0.23375*** | 0.61514 | 0.54656 | 0.68114* |
| # of grocery stores | | | | 0.76807*** | 0.57546*** | 0.56747*** | 0.66022* | 0.37656 | 0.43824 |
| # of restaurants | | | | 0.24331*** | 0.14464*** | 0.12700*** | -0.48827 | -0.25364 | -0.29559 |
| **Housing** | | | | | | | | | |
| % Homeowners | | | | -0.01007*** | -0.01001*** | -0.01043*** | -0.01313** | -0.01308** | -0.01400** |
| % Vacant Units | | | | 0.01230*** | 0.01291*** | 0.01231*** | 0.02416*** | 0.02573*** | 0.02567*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | | | | 0.51221*** | 0.51764*** | 0.49892*** | 0.69075*** | 0.74376*** | 0.66531*** |
| % Young People | | | | 0.00228 | 0.00062 | -0.00003 | -0.01511 | -0.01364 | -0.00635 |
| Ethnic Heterogeneity | | | | -0.00018 | -0.00105 | -0.00043 | -0.00792 | -0.00998 | -0.00841 |
| % Low-income | | | | 0.00407*** | 0.00459*** | 0.00511*** | 0.00958* | 0.01075* | 0.01029** |

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Table .33 – *Continued from previous page*

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | | | | 0.00694 | 0.00751 | -0.00422 | 0.00801 | -0.00305 | -0.00414 |
| % Residential LU | | | | 0.04430*** | 0.04347*** | 0.00940 | -0.03018 | -0.02381 | -0.03552 |
| % Retail LU | | | | 0.10248** | 0.11708*** | 0.04798* | 0.10012 | 0.10616 | 0.11499 |
| % Office LU | | | | -0.05635 | -0.02912 | -0.12662*** | -0.25269 | -0.20175 | -0.26593 |
| % School LU | | | | 0.06110 | 0.07284*** | 0.06594** | 0.10479 | 0.09764 | 0.11274 |
| # of bars | | | | -0.00281 | -0.00147 | -0.00440* | 0.02756* | 0.02297 | 0.02077 |
| # of grocery stores | | | | 0.00676* | 0.00405** | 0.00239 | -0.00690 | -0.00771 | -0.00949 |
| # of restaurants | | | | 0.00217* | 0.00157** | 0.00200*** | -0.00697 | -0.00577 | -0.00545 |
| **Housing** | | | | | | | | | |
| % Homeowners | | | | -0.01199 | -0.00599 | 0.00481 | -0.05362 | -0.03133 | -0.03222 |
| % Vacant Units | | | | 0.01571 | 0.00907 | 0.01244 | 0.03977 | 0.03756 | 0.03319 |
| **Time Varying** | | | | | | | | | |
| Logged Population | | | | -1.14688*** | -0.96418*** | -0.05305 | -0.08419 | -0.28912 | 0.14682 |
| % Young People | | | | -0.01947* | -0.01347** | -0.02069*** | -0.03689 | -0.01975 | -0.04776 |
| Ethnic Heterogeneity | | | | 0.03683*** | 0.03700*** | 0.04047*** | 0.00222 | 0.01123 | 0.00490 |
| % Low-income | | | | 0.03483*** | 0.04169*** | 0.01753*** | -0.03418 | -0.02031 | -0.01964 |
| Intercept | | | | 5.79593* | -7.62795*** | -15.16544*** | -0.09048 | -11.69210 | -15.26625 |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The ‘nightly’ and ‘day and night’ models include city and time interval fixed effects. The ‘yearly’ models also include city fixed effects. These are not included in the table for parsimony. No assault data available for Cincinnati.*

Table .34: Property Crime Models: Cincinnati

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.00692*** | 0.00381*** | 0.00029 | 0.00467* | 0.00440** | 0.00022 | 0.00822*** | 0.00544*** | 0.00021 |
| % Residential LU | -0.00875*** | -0.00754*** | -0.00580*** | -0.00585*** | -0.00534*** | -0.00466*** | -0.00185* | -0.00061 | -0.00018 |
| % Retail LU | 0.01942*** | 0.01674*** | 0.01457*** | 0.01094*** | 0.00978*** | 0.00625*** | 0.01137*** | 0.00835*** | 0.00366*** |
| % Office LU | 0.01550*** | 0.01230*** | 0.00661*** | 0.00717 | 0.00682* | -0.00086 | 0.01069*** | 0.01143*** | 0.00295 |
| % School LU | 0.00452* | 0.00283** | -0.00106 | 0.00286 | 0.00179 | -0.00138 | 0.00291 | 0.00273** | -0.00041 |
| # of bars | 0.20861* | 0.21510*** | 0.21328*** | 0.22080* | 0.22723** | 0.27725*** | 0.28063*** | 0.26672*** | 0.30541*** |
| # of grocery stores | 0.55856*** | 0.41805*** | 0.41123*** | 0.18096* | 0.19838*** | 0.24149*** | 0.26262*** | 0.20954*** | 0.27048*** |
| # of restaurants | 0.27685*** | 0.23778*** | 0.21693*** | 0.07674* | 0.06014** | 0.04027 | 0.13905*** | 0.08037*** | 0.06814*** |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00130 | -0.00153*** | -0.00216*** | -0.00432*** | -0.00451*** | -0.00570*** | -0.00409*** | -0.00393*** | -0.00563*** |
| % Vacant Units | 0.00477*** | 0.00650*** | 0.00600*** | 0.00940*** | 0.01033*** | 0.00902*** | 0.01295*** | 0.01523*** | 0.01289*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.57966*** | 0.58655*** | 0.59147*** | 0.62976*** | 0.69274*** | 0.61620*** | 0.66968*** | 0.73053*** | 0.61780*** |
| % Young People | 0.00175 | 0.00196** | 0.00270*** | -0.00284 | -0.00446** | -0.00269* | 0.00204 | 0.00205* | 0.00177* |
| Ethnic Heterogeneity | 0.00325** | 0.00366*** | 0.00392*** | 0.00138 | 0.00067 | 0.00215* | 0.00090 | 0.00006 | 0.00096 |
| % Low-income | 0.00097 | 0.00158*** | 0.00191*** | 0.00308** | 0.00257** | 0.00260*** | 0.00401*** | 0.00457*** | 0.00446*** |

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Table .34 – *Continued from previous page*

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.01309 | 0.00747* | 0.00219 | -0.01463 | -0.02256** | -0.02466*** | -0.03528*** | -0.02468*** | -0.02692*** |
| % Residential LU | 0.03079*** | 0.03428*** | 0.03092*** | -0.01692 | -0.02435** | -0.02296*** | -0.00717 | -0.00133 | -0.00775* |
| % Retail LU | 0.02455 | 0.03426** | 0.02353* | 0.08710** | 0.10047*** | 0.08489*** | 0.09575*** | 0.08405*** | 0.03173* |
| % Office LU | -0.00025 | 0.01478 | -0.02391 | -0.02648 | -0.05928 | -0.06130 | -0.04458 | -0.00963 | -0.05716** |
| % School LU | -0.05675* | -0.06106*** | -0.06020*** | -0.00112 | 0.01093 | 0.01170 | 0.01993 | -0.00219 | 0.00517 |
| # of bars | 0.00136 | 0.00069 | 0.00052 | -0.00699* | -0.00798** | -0.00763** | -0.00397 | -0.00508*** | -0.00624*** |
| # of grocery stores | -0.00164 | -0.00154 | -0.00005 | -0.00143 | -0.00262 | -0.00216 | 0.00390* | 0.00234* | 0.00279** |
| # of restaurants | 0.00091 | 0.00076** | 0.00078** | -0.00081 | -0.00070 | -0.00082 | -0.00105 | -0.00153*** | -0.00115** |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.01820* | -0.02403*** | -0.02907*** | 0.02767** | 0.02327** | 0.01924* | 0.02146** | 0.01446*** | 0.00062 |
| % Vacant Units | 0.01750 | 0.00579 | 0.01950*** | 0.01563 | 0.00977 | 0.01396 | 0.00687 | 0.00853 | 0.01249 |
| **Time Varying** | | | | | | | | | |
| Logged Population | -0.01211 | -0.14209 | -0.22227*** | 0.02538 | 0.15056 | 0.04388 | -0.58966*** | -0.53211*** | -0.36817*** |
| % Young People | 0.01696** | 0.01448*** | 0.01078*** | 0.01191 | 0.00390 | 0.00157 | 0.00699 | 0.00925** | -0.00220 |
| Ethnic Heterogeneity | -0.01703*** | -0.01624*** | -0.01209*** | 0.02775*** | 0.02639*** | 0.03018*** | 0.01621*** | 0.01077*** | 0.01443*** |
| % Low-income | 0.00639 | 0.00930*** | -0.00532** | 0.01614* | 0.01541** | 0.01136** | 0.02725*** | 0.02953*** | 0.01076*** |
| Intercept | -0.92593 | -9.63314*** | -8.17254*** | -5.69194* | -16.88333*** | -15.01489*** | 2.01504 | -8.80381*** | -7.89059*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. The 'yearly' models also include city fixed effects. These are not included in the table for parsimony.*

Table .35: Violent Crime Models: Columbus

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.00692*** | 0.00381*** | 0.00029 | 0.00467* | 0.00440** | 0.00022 | 0.00822*** | 0.00544*** | 0.00021 |
| % Residential LU | -0.00875*** | -0.00754*** | -0.00580*** | -0.00585*** | -0.00534*** | -0.00466*** | -0.00185* | -0.00061 | -0.00018 |
| % Retail LU | 0.01942*** | 0.01674*** | 0.01457*** | 0.01094*** | 0.00978*** | 0.00625*** | 0.01137*** | 0.00835*** | 0.00366*** |
| % Office LU | 0.01550*** | 0.01230*** | 0.00661*** | 0.00717 | 0.00682* | -0.00086 | 0.01069*** | 0.01143*** | 0.00295 |
| % School LU | 0.00452* | 0.00283** | -0.00106 | 0.00286 | 0.00179 | -0.00138 | 0.00291 | 0.00273** | -0.00041 |
| # of bars | 0.20861* | 0.21510*** | 0.21328*** | 0.22080* | 0.22723** | 0.27725*** | 0.28063*** | 0.26672*** | 0.30541*** |
| # of grocery stores | 0.55856*** | 0.41805*** | 0.41123*** | 0.18096* | 0.19838*** | 0.24149*** | 0.26262*** | 0.20954*** | 0.27048*** |
| # of restaurants | 0.27685*** | 0.23778*** | 0.21693*** | 0.07674* | 0.06014** | 0.04027 | 0.13905*** | 0.08037*** | 0.06814*** |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00130 | -0.00153*** | -0.00216*** | -0.00432*** | -0.00451*** | -0.00570*** | -0.00409*** | -0.00393*** | -0.00563*** |
| % Vacant Units | 0.00477*** | 0.00650*** | 0.00600*** | 0.00940*** | 0.01033*** | 0.00902*** | 0.01295*** | 0.01523*** | 0.01289*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.57966*** | 0.58655*** | 0.59147*** | 0.62976*** | 0.69274*** | 0.61620*** | 0.66968*** | 0.73053*** | 0.61780*** |
| % Young People | 0.00175 | 0.00196** | 0.00270*** | -0.00284 | -0.00446** | -0.00269* | 0.00204 | 0.00205* | 0.00177* |
| Ethnic Heterogeneity | 0.00325** | 0.00366*** | 0.00392*** | 0.00138 | 0.00067 | 0.00215* | 0.00090 | 0.00006 | 0.00096 |
| % Low-income | 0.00097 | 0.00158*** | 0.00191*** | 0.00308** | 0.00257** | 0.00260*** | 0.00401*** | 0.00457*** | 0.00446*** |

*Continued on next page*

Table .35 – *Continued from previous page*

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.01309 | 0.00747* | 0.00219 | -0.01463 | -0.02256** | -0.02466*** | -0.03528*** | -0.02468*** | -0.02692*** |
| % Residential LU | 0.03079*** | 0.03428*** | 0.03092*** | -0.01692 | -0.02435** | -0.02296*** | -0.00717 | -0.00133 | -0.00775* |
| % Retail LU | 0.02455 | 0.03426** | 0.02353* | 0.08710** | 0.10047*** | 0.08489*** | 0.09575*** | 0.08405*** | 0.03173* |
| % Office LU | -0.00025 | 0.01478 | -0.02391 | -0.02648 | -0.05928 | -0.06130 | -0.04458 | -0.00963 | -0.05716** |
| % School LU | -0.05675* | -0.06106*** | -0.06020*** | -0.00112 | 0.01093 | 0.01170 | 0.01993 | -0.00219 | 0.00517 |
| # of bars | 0.00136 | 0.00069 | 0.00052 | -0.00699* | -0.00798** | -0.00763** | -0.00397 | -0.00508*** | -0.00624*** |
| # of grocery stores | -0.00164 | -0.00154 | -0.00005 | -0.00143 | -0.00262 | -0.00216 | 0.00390* | 0.00234* | 0.00279** |
| # of restaurants | 0.00091 | 0.00076** | 0.00078** | -0.00081 | -0.00070 | -0.00082 | -0.00105 | -0.00153*** | -0.00115** |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.01820* | -0.02403*** | -0.02907*** | 0.02767** | 0.02327** | 0.01924* | 0.02146** | 0.01446*** | 0.00062 |
| % Vacant Units | 0.01750 | 0.00579 | 0.01950*** | 0.01563 | 0.00977 | 0.01396 | 0.00687 | 0.00853 | 0.01249 |
| **Time Varying** | | | | | | | | | |
| Logged Population | -0.01211 | -0.14209 | -0.22227*** | 0.02538 | 0.15056 | 0.04388 | -0.58966*** | -0.53211*** | -0.36817*** |
| % Young People | 0.01696** | 0.01448*** | 0.01078*** | 0.01191 | 0.00390 | 0.00157 | 0.00699 | 0.00925** | -0.00220 |
| Ethnic Heterogeneity | -0.01703*** | -0.01624*** | -0.01209*** | 0.02775*** | 0.02639*** | 0.03018*** | 0.01621*** | 0.01077*** | 0.01443*** |
| % Low-income | 0.00639 | 0.00930*** | -0.00532** | 0.01614* | 0.01541** | 0.01136** | 0.02725*** | 0.02953*** | 0.01076*** |
| Intercept | -0.92593 | -9.63314*** | -8.17254*** | -5.69194* | -16.88333*** | -15.01489*** | 2.01504 | -8.80381*** | -7.89059*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. The 'yearly' models also include city fixed effects. These are not included in the table for parsimony.*

Table .36: Property Crime Models: Columbus

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.01770*** | 0.01266*** | 0.00807*** | | | | 0.01134*** | 0.00866*** | 0.00448*** |
| % Residential LU | -0.00570*** | -0.00487*** | -0.00318*** | | | | -0.00062 | -0.00018 | 0.00135*** |
| % Retail LU | 0.01747*** | 0.01432*** | 0.01210*** | | | | 0.01084*** | 0.00624*** | 0.00427*** |
| % Office LU | 0.01582*** | 0.00996*** | 0.00308*** | | | | 0.00967*** | 0.00726*** | -0.00020 |
| % School LU | 0.00544*** | 0.00490*** | 0.00139* | | | | 0.00528*** | 0.00457*** | 0.00097 |
| # of bars | 0.10614* | 0.03158 | 0.02973 | | | | 0.18200** | 0.11379*** | 0.11235*** |
| # of grocery stores | 0.45237*** | 0.31415*** | 0.35864*** | | | | 0.13312** | 0.13923*** | 0.20851*** |
| # of restaurants | 0.24326*** | 0.17876*** | 0.16610*** | | | | 0.09110*** | 0.06084*** | 0.05096*** |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00689*** | -0.00646*** | -0.00654*** | | | | -0.00510*** | -0.00482*** | -0.00572*** |
| % Vacant Units | 0.00867*** | 0.00929*** | 0.00891*** | | | | 0.01345*** | 0.01445*** | 0.01316*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.72770*** | 0.69611*** | 0.63239*** | | | | 0.79517*** | 0.78504*** | 0.66134*** |
| % Young People | 0.00042 | 0.00011 | 0.00082* | | | | 0.00248** | 0.00245*** | 0.00149** |
| Ethnic Heterogeneity | -0.00061 | 0.00072* | 0.00143*** | | | | 0.00103 | 0.00132** | 0.00215*** |
| % Low-income | -0.00049 | -0.00005 | 0.00137*** | | | | 0.00013 | 0.00113** | 0.00168*** |

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Table .36 – *Continued from previous page*

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.01548*** | 0.01695*** | 0.01634*** | | | | 0.01074*** | 0.01007*** | 0.01024*** |
| % Residential LU | -0.00471* | -0.00208 | 0.00027 | | | | -0.00154 | -0.00155 | 0.00138 |
| % Retail LU | 0.02917*** | 0.02409*** | 0.02805*** | | | | 0.03813*** | 0.03253*** | 0.04270*** |
| % Office LU | -0.01804* | -0.01164* | -0.01230** | | | | -0.01590 | -0.01370 | -0.01223 |
| % School LU | -0.01537* | -0.02496*** | -0.02611*** | | | | -0.00940 | -0.01686** | -0.02023*** |
| # of bars | 0.00554*** | 0.00528*** | 0.00625*** | | | | 0.00508*** | 0.00599*** | 0.00566*** |
| # of grocery stores | 0.00543*** | 0.00648*** | 0.00744*** | | | | 0.00303* | 0.00356*** | 0.00555*** |
| # of restaurants | -0.00101* | -0.00101*** | -0.00152*** | | | | -0.00158** | -0.00173*** | -0.00216*** |
| **Housing** | | | | | | | | | |
| % Homeowners | 0.01189*** | 0.00960*** | 0.00882*** | | | | 0.01631*** | 0.01415*** | 0.01196*** |
| % Vacant Units | -0.01232* | -0.02225*** | -0.01541*** | | | | 0.03232*** | 0.02026*** | 0.02900*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.43047*** | 0.28827*** | 0.12628*** | | | | 0.34724*** | 0.32624*** | 0.09713* |
| % Young People | -0.00909*** | -0.00728*** | -0.00456*** | | | | 0.00431 | 0.00361 | 0.00849*** |
| Ethnic Heterogeneity | -0.00033 | -0.00048 | 0.00117 | | | | 0.00015 | 0.00100 | 0.00230 |
| % Low-income | 0.02912*** | 0.02726*** | 0.02290*** | | | | 0.03230*** | 0.03029*** | 0.02373*** |
| Intercept | -6.85881*** | -15.44545*** | -13.49112*** | | | | -9.09645*** | -18.75821*** | -15.58049*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. The 'yearly' models also include city fixed effects. These are not included in the table for parsimony. No motor theft for Columbus.*

Table .37: Violent Crime Models: Fresno

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.01029** | 0.00946*** | 0.00595* | -0.00325 | -0.00295 | -0.00628 | 0.01558 | 0.01348 | 0.01146 |
| % Residential LU | -0.00637*** | -0.00438*** | -0.00260* | -0.01504*** | -0.01342*** | -0.01188*** | -0.00768 | -0.00685 | -0.00639 |
| % Retail LU | 0.00443 | 0.00521** | 0.00424* | 0.01321*** | 0.01260*** | 0.01150*** | -0.00462 | -0.00267 | -0.00909 |
| % Office LU | 0.00069 | 0.00568* | 0.00352 | -0.00136 | 0.00314 | 0.00087 | -0.00797 | 0.00355 | 0.00509 |
| % School LU | -0.00667 | -0.00221 | -0.00227 | 0.00768 | 0.00461 | 0.00229 | -0.06010 | -0.05770 | -0.05426 |
| # of bars | -0.12199 | -0.17984 | -0.17280 | -0.12142 | -0.08376 | -0.06390 | 0.15679 | -0.25148 | |
| # of grocery stores | 0.39418*** | 0.30425*** | 0.30721*** | 0.59522*** | 0.42701*** | 0.42745*** | 0.50815 | 0.42873 | 0.45952 |
| # of restaurants | 0.11328** | 0.08483*** | 0.08497*** | 0.23282*** | 0.16341*** | 0.15722*** | 0.13925 | 0.13590 | 0.21111 |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00585*** | -0.00539*** | -0.00692*** | -0.00359* | -0.00354** | -0.00435*** | -0.01165* | -0.00978 | -0.01096* |
| % Vacant Units | 0.00693* | 0.01046*** | 0.01005*** | 0.00298 | 0.00375 | 0.00368 | 0.01383 | 0.01186 | 0.01484 |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.69771*** | 0.68415*** | 0.60750*** | 0.54777*** | 0.52734*** | 0.48879*** | 0.64322*** | 0.71565*** | 0.67589*** |
| % Young People | 0.00179 | -0.00102 | -0.00025 | -0.00255 | -0.00269 | -0.00088 | 0.00446 | 0.00327 | -0.00608 |
| Ethnic Heterogeneity | -0.00025 | -0.00014 | 0.00209 | 0.00017 | -0.00025 | -0.00012 | -0.00725 | -0.00753 | -0.00272 |
| % Low-income | 0.00798*** | 0.00851*** | 0.00906*** | 0.00639** | 0.00576*** | 0.00645*** | 0.00127 | 0.00203 | 0.00223 |

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Table .37 – *Continued from previous page*

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.01527 | 0.00750 | 0.02443** | 0.02206 | 0.01357 | 0.02289* | -0.03038 | -0.01784 | 0.01139 |
| % Residential LU | -0.01291 | -0.01277 | 0.00659 | 0.02330* | 0.01612 | 0.02384*** | -0.00503 | 0.00383 | 0.03678 |
| % Retail LU | 0.01874 | 0.00112 | 0.02154 | 0.06484* | 0.03739 | 0.04583 | 0.18964 | 0.19112 | 0.22552 |
| % Office LU | -0.03513 | -0.02558 | -0.04671 | -0.23165*** | -0.20059*** | -0.22214*** | -0.17925 | -0.17817 | -0.16597 |
| % School LU | -0.11461 | -0.09905 | -0.04337 | -0.22505* | -0.25473** | -0.21637** | -0.12494 | -0.15158 | -0.12856 |
| # of bars | -0.00045 | -0.00408 | -0.00761 | 0.00848 | 0.00643 | 0.00691 | -0.03464 | -0.03170 | -0.03094 |
| # of grocery stores | 0.00471 | 0.00407 | 0.00387 | -0.00060 | 0.00094 | 0.00149 | -0.00927 | -0.01092 | -0.01355 |
| # of restaurants | -0.00141 | -0.00054 | -0.00042 | -0.00120 | -0.00030 | -0.00063 | -0.00513 | -0.00383 | -0.00466 |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.03686** | -0.04177*** | -0.04651*** | -0.07054*** | -0.06910*** | -0.07423*** | -0.00928 | 0.00102 | 0.00618 |
| % Vacant Units | -0.05604 | -0.05708 | -0.05413 | -0.03942 | -0.07053 | -0.06832 | 0.19510 | 0.23762 | 0.25629 |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.65467* | 0.59852* | -0.06581 | -0.11944 | -0.02666 | -0.29182 | 1.38089 | 1.15705 | 0.42864 |
| % Young People | 0.00479 | -0.00124 | 0.00826 | 0.01630 | 0.01548 | 0.02315 | -0.05504 | -0.05803 | -0.03365 |
| Ethnic Heterogeneity | 0.03243*** | 0.02970*** | 0.02476*** | 0.02338* | 0.02473** | 0.02686*** | 0.09969* | 0.10000* | 0.08990* |
| % Low-income | 0.00869 | 0.00691 | 0.00862 | 0.00113 | 0.00262 | -0.00033 | 0.08889 | 0.10295* | 0.12448** |
| Intercept | -10.30211*** | -19.94201*** | -13.41978*** | -0.81861 | -11.89341*** | -9.41209*** | -29.27168 | -41.46112** | -36.07512* |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. The 'yearly' models also include city fixed effects. These are not included in the table for parsimony.*

Table .38: Property Crime Models: Fresno

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.00448 | 0.00074 | -0.00297* | 0.00702* | 0.00611*** | 0.00333 | 0.00861*** | 0.00587*** | 0.00048 |
| % Residential LU | -0.01148*** | -0.01093*** | -0.00856*** | -0.00808*** | -0.00578*** | -0.00445*** | -0.00615*** | -0.00572*** | -0.00344*** |
| % Retail LU | 0.01679*** | 0.01925*** | 0.01785*** | 0.00592** | 0.00787*** | 0.00571*** | 0.00621*** | 0.00629*** | 0.00430*** |
| % Office LU | 0.01224*** | 0.01149*** | 0.00713*** | 0.00308 | 0.00372* | 0.00043 | 0.01489*** | 0.00999*** | 0.00620*** |
| % School LU | 0.01059 | 0.00892*** | 0.00826*** | 0.00625 | 0.00536 | 0.00504 | 0.00644 | 0.00405 | 0.00472 |
| # of bars | 0.01134 | 0.05694 | 0.07545 | -0.20273 | -0.00703 | -0.00275 | -0.10683 | -0.03667 | 0.01761 |
| # of grocery stores | 0.32456*** | 0.14742*** | 0.13866*** | 0.12966 | 0.03084 | 0.05008 | 0.24959*** | 0.17534*** | 0.19367*** |
| # of restaurants | 0.21085*** | 0.17025*** | 0.17668*** | 0.16618*** | 0.08835*** | 0.08891*** | 0.17643*** | 0.12078*** | 0.13971*** |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00318*** | -0.00315*** | -0.00429*** | -0.00463*** | -0.00472*** | -0.00598*** | -0.00241*** | -0.00230*** | -0.00520*** |
| % Vacant Units | -0.00011 | -0.00159 | -0.00152 | -0.00169 | -0.00294 | -0.00229 | 0.00591** | 0.00588*** | 0.00593*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.56687*** | 0.59025*** | 0.53116*** | 0.67034*** | 0.70660*** | 0.65149*** | 0.57414*** | 0.60019*** | 0.45583*** |
| % Young People | -0.00153 | -0.00390*** | -0.00203* | 0.00186 | -0.00012 | 0.00086 | -0.00114 | -0.00099 | -0.00130 |
| Ethnic Heterogeneity | -0.00092 | -0.00065 | 0.00113 | -0.00168 | -0.00217* | -0.00027 | -0.00014 | 0.00026 | 0.00293*** |
| % Low-income | 0.00103 | 0.00138* | 0.00284*** | 0.00168 | 0.00156* | 0.00133 | 0.00127 | 0.00171* | 0.00146* |

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Table .38 – *Continued from previous page*

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.01642** | 0.00855* | 0.00867* | 0.03390*** | 0.03315*** | 0.03372*** | 0.00735 | 0.00406 | 0.01219** |
| % Residential LU | 0.01909*** | 0.01953*** | 0.02419*** | 0.01197* | 0.01484*** | 0.02037*** | 0.01536*** | 0.01421*** | 0.02557*** |
| % Retail LU | 0.07163*** | 0.08930*** | 0.09740*** | -0.00137 | 0.01606 | 0.02374* | -0.01470 | -0.02577** | -0.01135 |
| % Office LU | -0.05548* | -0.06906*** | -0.08306*** | -0.03661 | -0.05785*** | -0.06206*** | -0.03237 | -0.01725 | -0.03281* |
| % School LU | -0.09325 | -0.10938*** | -0.12030*** | -0.13336* | -0.09657** | -0.08452* | -0.18082*** | -0.14913*** | -0.11270*** |
| # of bars | 0.00647 | 0.00595* | 0.00807*** | -0.00430 | -0.00872* | -0.00974** | 0.00317 | -0.00162 | -0.00086 |
| # of grocery stores | -0.00010 | -0.00181 | -0.00342** | 0.00936*** | 0.00831*** | 0.00653*** | -0.00055 | -0.00115 | -0.00274* |
| # of restaurants | -0.00194* | -0.00180*** | -0.00156** | -0.00169 | -0.00080 | -0.00046 | -0.00036 | 0.00151** | 0.00190*** |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.05253*** | -0.04733*** | -0.03699*** | -0.04887*** | -0.04453*** | -0.03322*** | -0.07901*** | -0.07029*** | -0.06382*** |
| % Vacant Units | -0.12120*** | -0.12230*** | -0.13705*** | -0.10888*** | -0.08346*** | -0.09000*** | -0.11292*** | -0.09651*** | -0.13659*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | -0.09189 | -0.17992* | -0.28626*** | 0.23060 | 0.02962 | -0.10459 | -0.24931 | -0.38287*** | -0.77237*** |
| % Young People | -0.03008** | -0.03007*** | -0.00621 | 0.04699*** | 0.04222*** | 0.05403*** | -0.04788*** | -0.03920*** | -0.00615 |
| Ethnic Heterogeneity | 0.04250*** | 0.04367*** | 0.03801*** | 0.05265*** | 0.04909*** | 0.04390*** | 0.02855*** | 0.02389*** | 0.01794*** |
| % Low-income | -0.01222* | -0.00374 | 0.00114 | -0.01237* | -0.00970* | 0.00116 | -0.01668** | -0.01234*** | -0.00576* |
| Intercept | 1.33799 | -8.62219*** | -8.54287*** | -5.87938*** | -15.10371*** | -14.65869*** | 5.46053*** | -3.89495*** | -0.49618 |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. The 'yearly' models also include city fixed effects. These are not included in the table for parsimony.*

Table .39: Violent Crime Models: Glendale

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.01157 | 0.01147** | 0.00939* | 0.01172 | 0.01381** | 0.01149** | 0.02524 | 0.02429 | 0.02322 |
| % Residential LU | -0.00872*** | -0.00909*** | -0.00815*** | -0.01356*** | -0.01314*** | -0.01225*** | -0.01085 | -0.01031 | -0.00809 |
| % Retail LU | 0.01894*** | 0.00913*** | 0.00917*** | 0.02348*** | 0.01224*** | 0.01210*** | -0.00870 | -0.00818 | -0.00506 |
| % Office LU | 0.00128 | 0.01171 | 0.00343 | 0.04608** | 0.03755*** | 0.02949*** | -0.30982 | -0.30072 | -0.30402 |
| % School LU | 0.01969*** | 0.01658*** | 0.01344*** | 0.01346* | 0.01198*** | 0.00869* | 0.00364 | 0.00268 | 0.00329 |
| # of bars | 0.97843*** | 0.79771*** | 0.76105*** | 1.04110*** | 0.48265*** | 0.42115*** | 1.66928 | 1.61408 | 1.62996 |
| # of grocery stores | 0.15577 | 0.21747 | 0.23559* | 0.68463** | 0.64489*** | 0.70280*** | 0.00082 | 0.03953 | -0.02008 |
| # of restaurants | 0.31288*** | 0.33570*** | 0.31727*** | 0.44916*** | 0.46935*** | 0.44946*** | -1.41596 | -1.36628 | -1.41497 |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00660** | -0.00657*** | -0.00730*** | -0.00756** | -0.00629*** | -0.00710*** | 0.00184 | 0.00189 | -0.00197 |
| % Vacant Units | 0.00557 | 0.00198 | 0.00364 | 0.00335 | -0.00073 | 0.00334 | 0.03049 | 0.02769 | 0.02687 |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.50689*** | 0.49780*** | 0.44936*** | 0.57454*** | 0.57896*** | 0.50381*** | 0.83339** | 0.80525** | 0.61516** |
| % Young People | -0.00365 | -0.00616 | -0.00822* | -0.00627 | -0.00842 | -0.00605 | 0.02389 | 0.02340 | -0.00415 |
| Ethnic Heterogeneity | 0.00523 | 0.00490* | 0.00581* | 0.00281 | -0.00091 | 0.00161 | -0.00728 | -0.00708 | -0.00481 |
| % Low-income | -0.00118 | -0.00038 | 0.00207 | 0.00303 | 0.00134 | 0.00181 | -0.00472 | -0.00481 | -0.01396 |

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Table .39 – *Continued from previous page*

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | -0.11435* | -0.10149** | -0.09801** | -0.16190* | -0.10224* | -0.05192 | -0.19876 | -0.19530 | -0.18539 |
| % Residential LU | 0.01006 | 0.01876 | 0.01869 | 0.03132 | 0.02798 | 0.02571* | 0.04453 | 0.04086 | 0.06535 |
| % Retail LU | 0.16380** | 0.14167** | 0.12170** | 0.20617** | 0.13210* | 0.10896* | -0.13547 | -0.12964 | -0.08761 |
| % Office LU | -0.29184 | -0.18188 | -0.14293 | -0.76786** | -0.47244** | -0.48324** | 0.69793 | 0.68019 | 0.56011 |
| % School LU | 0.07038 | 0.04531 | 0.05659 | 0.16219* | 0.11838** | 0.13003** | -0.14488 | -0.13410 | -0.07272 |
| # of bars | 0.00137 | 0.00211 | 0.00016 | 0.01413 | 0.00537 | 0.00498 | -0.07406 | -0.07320 | -0.06053 |
| # of grocery stores | -0.02012 | -0.02065** | -0.02183** | -0.01644 | -0.01626* | -0.01398 | -0.05244 | -0.04925 | -0.05502 |
| # of restaurants | -0.00867* | -0.00786** | -0.00745* | -0.01065* | -0.00539 | -0.00415 | 0.01445 | 0.01400 | 0.01407 |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.01489 | -0.02074 | -0.03093* | -0.04333 | -0.02151 | -0.02222 | 0.12883 | 0.12288 | 0.08283 |
| % Vacant Units | -0.02358 | -0.04441 | -0.03563 | -0.03629 | -0.08647 | -0.05077 | -0.25569 | -0.25243 | -0.19445 |
| **Time Varying** | | | | | | | | | |
| Logged Population | -0.50027 | -0.39645 | -0.45358 | -0.92163 | -0.19198 | 0.33237 | -1.97516 | -1.87349 | -3.81295 |
| % Young People | -0.00630 | 0.01028 | -0.04974 | -0.07505 | 0.09367 | 0.07762* | 0.06888 | 0.06762 | 0.06030 |
| Ethnic Heterogeneity | 0.00658 | 0.00665 | 0.00454 | 0.00792 | 0.01687* | 0.01231 | 0.00968 | 0.01051 | -0.01920 |
| % Low-income | 0.07780** | 0.07559*** | 0.06899*** | 0.08085* | 0.08083** | 0.05394** | 0.38143* | 0.36794* | 0.38296*** |
| Intercept | 1.74277 | -10.40477 | -7.70877 | 8.03933 | -15.33507 | -20.37725*** | -2.51666 | -13.48468 | 9.24052 |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. The 'yearly' models also include city fixed effects. These are not included in the table for parsimony.*

Table .40: Property Crime Models: Glendale

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.00825 | 0.02346*** | 0.02098*** | 0.01181 | 0.01156*** | 0.00837* | 0.01744*** | 0.01405*** | 0.00842*** |
| % Residential LU | -0.00841*** | -0.00971*** | -0.00842*** | -0.00370** | -0.00465*** | -0.00370*** | -0.00260** | -0.00391*** | -0.00293*** |
| % Retail LU | 0.04073*** | 0.02888*** | 0.02672*** | 0.01488*** | 0.00836*** | 0.00753*** | 0.01948*** | 0.01175*** | 0.01096*** |
| % Office LU | 0.01434 | 0.00606 | 0.00083 | 0.02866* | 0.01608** | 0.00803 | 0.02956** | 0.02017*** | 0.01349*** |
| % School LU | 0.01863*** | 0.01328*** | 0.00850*** | 0.00910* | 0.00601* | 0.00335 | 0.02029*** | 0.01538*** | 0.01270*** |
| # of bars | 0.93561*** | 0.98351*** | 0.98310*** | 0.52262* | 0.39201*** | 0.36783*** | 0.38915* | 0.33757*** | 0.32075*** |
| # of grocery stores | 0.60500** | 0.58823*** | 0.69917*** | 0.25072 | 0.24557** | 0.31610*** | 0.06194 | 0.07921 | 0.15249** |
| # of restaurants | 0.39014*** | 0.38997*** | 0.37431*** | 0.27738*** | 0.30448*** | 0.27087*** | 0.29884*** | 0.33339*** | 0.31636*** |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00890*** | -0.00420*** | -0.00499*** | -0.01006*** | -0.00908*** | -0.01046*** | -0.00266* | -0.00135* | -0.00309*** |
| % Vacant Units | -0.00950** | -0.00688*** | -0.00466* | -0.00586 | -0.00435 | -0.00273 | -0.00275 | -0.00124 | -0.00050 |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.55988*** | 0.64031*** | 0.59585*** | 0.55735*** | 0.60867*** | 0.54970*** | 0.61354*** | 0.67515*** | 0.54002*** |
| % Young People | -0.00118 | -0.01017*** | -0.01199*** | 0.01238** | 0.01063*** | 0.00516* | 0.00456 | -0.00041 | -0.00352** |
| Ethnic Heterogeneity | 0.00121 | 0.00189 | 0.00263* | -0.00403 | -0.00212 | 0.00012 | -0.00484** | -0.00213* | -0.00029 |
| % Low-income | 0.00697* | 0.01089*** | 0.00942*** | 0.00302 | 0.00200 | 0.00172 | -0.00375 | -0.00417*** | -0.00244** |

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Table .40 – *Continued from previous page*

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | -0.02055 | -0.01365 | -0.00372 | -0.12605*** | -0.09519*** | -0.09195*** | -0.07572** | -0.05878*** | -0.07368*** |
| % Residential LU | 0.02889** | 0.03638*** | 0.03475*** | 0.01671 | 0.02043* | 0.01727* | -0.01477* | 0.00036 | 0.00178 |
| % Retail LU | 0.14433*** | 0.12813*** | 0.12473*** | 0.12648** | 0.09918*** | 0.10127*** | 0.00231 | -0.02359 | -0.00897 |
| % Office LU | -0.37889*** | -0.32444*** | -0.24824*** | -0.09225 | -0.03594 | -0.02663 | -0.05994 | 0.00267 | 0.00715 |
| % School LU | 0.03441 | 0.01941 | 0.03870* | 0.03727 | 0.00571 | 0.00545 | 0.00599 | -0.02720* | -0.02412 |
| # of bars | 0.01108 | 0.01793*** | 0.01402** | 0.00185 | -0.00010 | 0.00002 | 0.00225 | -0.00440 | -0.00442 |
| # of grocery stores | -0.01588* | -0.01478*** | -0.01309*** | -0.02138* | -0.02284*** | -0.02256*** | -0.01395* | -0.01335*** | -0.01229*** |
| # of restaurants | -0.00785** | -0.00594*** | -0.00588*** | -0.00786** | -0.00426* | -0.00496** | -0.00098 | 0.00135 | 0.00000 |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.01358 | 0.01423 | 0.01860** | -0.00964 | -0.00845 | -0.00727 | -0.03379** | -0.03288*** | -0.03568*** |
| % Vacant Units | -0.11217* | -0.02342 | 0.00952 | 0.05010 | 0.04886 | 0.04309 | -0.10654** | -0.09603*** | -0.12760*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | -0.54257 | -0.82813*** | -0.57564*** | 0.64953 | 0.69309 | 0.92883** | 0.91066* | 0.31178 | 0.04630 |
| % Young People | -0.06186 | -0.00733 | -0.01868 | -0.07664 | -0.05304 | -0.04960* | -0.06354* | -0.06408*** | -0.07567*** |
| Ethnic Heterogeneity | 0.00958 | 0.00892* | 0.00629 | 0.01009 | 0.00851 | 0.00693 | 0.01299* | 0.01243*** | 0.00979*** |
| % Low-income | 0.05647** | 0.05215*** | 0.04066*** | 0.02037 | 0.01763 | 0.01166 | 0.02902* | 0.03895*** | 0.04803*** |
| Intercept | 5.67252 | -6.23909* | -8.95306*** | -8.90084 | -21.02508*** | -22.69146*** | -6.36336 | -11.16912*** | -6.85029*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. The 'yearly' models also include city fixed effects. These are not included in the table for parsimony.*

Table .41: Violent Crime Models: Houston

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.00325* | 0.00407*** | 0.00280*** | 0.00352* | 0.00511*** | 0.00437*** | 0.00896* | 0.00816* | 0.00781* |
| % Residential LU | -0.00616*** | -0.00528*** | -0.00471*** | -0.00936*** | -0.00707*** | -0.00630*** | -0.00624*** | -0.00596*** | -0.00562*** |
| % Retail LU | 0.00978*** | 0.00844*** | 0.00633*** | 0.02080*** | 0.01633*** | 0.01510*** | 0.00602 | 0.00520 | 0.00363 |
| % Office LU | 0.00570 | 0.00367 | -0.00067 | 0.00323 | 0.00138 | -0.00113 | 0.01366 | 0.01600* | 0.01329 |
| % School LU | 0.00687** | 0.00676*** | 0.00269* | 0.00350 | 0.00382** | 0.00042 | -0.00266 | -0.00257 | -0.00759 |
| # of bars | 0.62291*** | 0.53456*** | 0.55387*** | 0.33840*** | 0.31027*** | 0.32389*** | 0.75378*** | 0.62502*** | 0.62868*** |
| # of grocery stores | 0.35990*** | 0.31549*** | 0.33782*** | 0.70422*** | 0.54699*** | 0.54745*** | 0.22275 | 0.19862 | 0.20871 |
| # of restaurants | 0.21782*** | 0.19073*** | 0.18825*** | 0.31892*** | 0.26039*** | 0.25126*** | 0.17510** | 0.12161* | 0.11908* |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.01193*** | -0.01084*** | -0.01093*** | -0.01037*** | -0.00949*** | -0.00925*** | -0.00743*** | -0.00706*** | -0.00725*** |
| % Vacant Units | 0.00884*** | 0.00956*** | 0.00928*** | 0.00808*** | 0.00869*** | 0.00862*** | 0.01181** | 0.01242*** | 0.01286*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.52779*** | 0.54757*** | 0.50803*** | 0.47050*** | 0.48650*** | 0.46769*** | 0.53130*** | 0.52835*** | 0.51186*** |
| % Young People | -0.00331** | -0.00521*** | -0.00304*** | -0.00316* | -0.00364*** | -0.00065 | 0.00047 | 0.00130 | 0.00082 |
| Ethnic Heterogeneity | 0.00138 | 0.00070 | 0.00023 | 0.00001 | -0.00160*** | -0.00173*** | -0.00131 | -0.00237 | -0.00384 |
| % Low-income | 0.00528*** | 0.00452*** | 0.00529*** | 0.00512*** | 0.00412*** | 0.00473*** | 0.00579* | 0.00679* | 0.00706** |

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Table .41 – *Continued from previous page*

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | -0.01500*** | -0.01556*** | -0.01677*** | 0.00465 | 0.00685** | 0.00578* | 0.00564 | 0.00953 | 0.01145 |
| % Residential LU | 0.00172 | 0.00074 | -0.00116 | 0.01437*** | 0.01352*** | 0.01183*** | 0.00636 | 0.00714 | 0.00786 |
| % Retail LU | 0.00058 | 0.00047 | -0.00049 | 0.01615*** | 0.01592*** | 0.01497*** | 0.01271 | 0.01715** | 0.01822** |
| % Office LU | -0.03766* | -0.06990*** | -0.07570*** | 0.02713 | 0.00115 | -0.00094 | -0.04529 | -0.03433 | -0.03288 |
| % School LU | 0.04129** | 0.03578*** | 0.05175*** | 0.02795 | 0.01752 | 0.02810** | -0.01786 | -0.01000 | -0.01821 |
| # of bars | 0.00698*** | 0.00738*** | 0.00856*** | 0.00473** | 0.00539*** | 0.00688*** | 0.00828 | 0.00600 | 0.00534 |
| # of grocery stores | -0.00555*** | -0.00617*** | -0.00487*** | -0.00629*** | -0.00620*** | -0.00486*** | -0.01070** | -0.01003** | -0.00829* |
| # of restaurants | -0.00019 | -0.00021 | -0.00112*** | 0.00131** | 0.00078*** | -0.00002 | 0.00105 | 0.00135 | 0.00075 |
| **Housing** | | | | | | | | | |
| % Homeowners | 0.01985*** | 0.01933*** | 0.00762*** | 0.00748* | 0.00403* | -0.00587** | 0.01939 | 0.01908* | 0.01531 |
| % Vacant Units | 0.01972*** | 0.02271*** | 0.02490*** | -0.00589 | -0.00891* | -0.00604 | 0.03589 | 0.03207 | 0.03532* |
| **Time Varying** | | | | | | | | | |
| Logged Population | -0.10388 | -0.05362 | -0.05689 | -0.09428 | -0.06814 | -0.10104* | -0.06112 | -0.05841 | -0.05155 |
| % Young People | 0.03331*** | 0.02525*** | 0.00398 | 0.03368*** | 0.02495*** | 0.01006* | 0.00348 | -0.00062 | 0.00197 |
| Ethnic Heterogeneity | 0.00164 | 0.00318*** | 0.00233** | 0.00393* | 0.00548*** | 0.00551*** | 0.01136* | 0.01093* | 0.01023* |
| % Low-income | 0.04853*** | 0.04837*** | 0.03843*** | 0.05279*** | 0.05125*** | 0.04447*** | 0.05915*** | 0.05479*** | 0.04838*** |
| Intercept | -3.71725*** | -15.06043*** | -13.09245*** | -4.43864*** | -15.18143*** | -13.46644*** | -9.18197** | -19.87253*** | -19.39212*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. The 'yearly' models also include city fixed effects. These are not included in the table for parsimony.*

Table .42: Property Crime Models: Houston

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.00597*** | 0.00561*** | 0.00452*** | 0.00734*** | 0.00891*** | 0.00819*** | 0.00487*** | 0.00590*** | 0.00376*** |
| % Residential LU | -0.00777*** | -0.00771*** | -0.00635*** | -0.00658*** | -0.00523*** | -0.00430*** | -0.00458*** | -0.00455*** | -0.00330*** |
| % Retail LU | 0.01379*** | 0.01215*** | 0.01062*** | 0.00758*** | 0.00772*** | 0.00678*** | 0.00629*** | 0.00549*** | 0.00311*** |
| % Office LU | 0.01033*** | 0.00864*** | 0.00465*** | 0.00463 | 0.00389* | 0.00037 | 0.00169 | 0.00089 | -0.00375** |
| % School LU | 0.00737*** | 0.00715*** | 0.00326*** | 0.00605* | 0.00694*** | 0.00289* | 0.00255 | 0.00321*** | -0.00122 |
| # of bars | 0.31409*** | 0.34695*** | 0.37663*** | 0.59220*** | 0.52085*** | 0.53112*** | 0.09745 | 0.13140*** | 0.15498*** |
| # of grocery stores | 0.39841*** | 0.33126*** | 0.32492*** | 0.34493*** | 0.27976*** | 0.27302*** | 0.28349*** | 0.24347*** | 0.27194*** |
| # of restaurants | 0.34750*** | 0.31845*** | 0.30539*** | 0.25052*** | 0.22213*** | 0.21329*** | 0.18282*** | 0.17679*** | 0.19844*** |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00498*** | -0.00403*** | -0.00375*** | -0.01079*** | -0.01009*** | -0.00960*** | -0.00742*** | -0.00660*** | -0.00701*** |
| % Vacant Units | 0.00200** | 0.00341*** | 0.00362*** | 0.00193 | 0.00287*** | 0.00306*** | 0.00640*** | 0.00789*** | 0.00819*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.49247*** | 0.49387*** | 0.48549*** | 0.47555*** | 0.51649*** | 0.51731*** | 0.50383*** | 0.53957*** | 0.46854*** |
| % Young People | 0.00191* | 0.00243*** | 0.00393*** | 0.00170 | 0.00164* | 0.00457*** | -0.00265** | -0.00273*** | -0.00126** |
| Ethnic Heterogeneity | 0.00313*** | 0.00312*** | 0.00315*** | 0.00369*** | 0.00254*** | 0.00175*** | 0.00439*** | 0.00462*** | 0.00445*** |
| % Low-income | -0.00010 | -0.00038 | 0.00148*** | 0.00213* | 0.00164*** | 0.00227*** | 0.00060 | 0.00111*** | 0.00173*** |

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Table .42 – *Continued from previous page*

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | -0.00124 | 0.00125 | 0.00002 | -0.00037 | 0.00451* | 0.00375* | -0.00503* | -0.00561*** | -0.00813*** |
| % Residential LU | 0.01035*** | 0.00945*** | 0.00682*** | 0.01035*** | 0.00854*** | 0.00440*** | 0.00561*** | 0.00383*** | 0.00429*** |
| % Retail LU | 0.01429*** | 0.01312*** | 0.01076*** | 0.01413*** | 0.01333*** | 0.01043*** | 0.00793*** | 0.00642*** | 0.00707*** |
| % Office LU | 0.04182*** | 0.02060*** | 0.01214** | 0.10473*** | 0.05286*** | 0.03481*** | -0.03979*** | -0.05353*** | -0.05533*** |
| % School LU | 0.01871 | 0.01992*** | 0.02407*** | -0.03199* | -0.02806** | -0.01846* | 0.05655*** | 0.05019*** | 0.05985*** |
| # of bars | 0.00052 | 0.00082 | 0.00326*** | 0.00093 | 0.00180* | 0.00509*** | 0.00128 | 0.00267*** | 0.00365*** |
| # of grocery stores | -0.00455*** | -0.00567*** | -0.00608*** | -0.00705*** | -0.00774*** | -0.00878*** | -0.01153*** | -0.01198*** | -0.01089*** |
| # of restaurants | 0.00206*** | 0.00198*** | 0.00148*** | 0.00161*** | 0.00133*** | 0.00044* | 0.00082** | 0.00055*** | 0.00020 |
| **Housing** | | | | | | | | | |
| % Homeowners | 0.00284 | 0.00047 | -0.00184* | 0.01467*** | 0.01092*** | 0.00414** | 0.00084 | 0.00155 | -0.00249* |
| % Vacant Units | 0.00320 | 0.00945*** | 0.01518*** | -0.02160*** | -0.01536*** | -0.00829* | 0.00949* | 0.01724*** | 0.01636*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | -0.40486*** | -0.39604*** | -0.29256*** | -0.23307*** | -0.14888*** | 0.03991 | -0.07359 | -0.03697 | -0.17146*** |
| % Young People | 0.04052*** | 0.03086*** | 0.02038*** | 0.06849*** | 0.04953*** | 0.03103*** | 0.02854*** | 0.01857*** | 0.01658*** |
| Ethnic Heterogeneity | -0.00546*** | -0.00484*** | -0.00374*** | -0.00552*** | -0.00306*** | -0.00069 | 0.00418*** | 0.00453*** | 0.00405*** |
| % Low-income | 0.01216*** | 0.01051*** | 0.00620*** | 0.03864*** | 0.03614*** | 0.03238*** | 0.02913*** | 0.02777*** | 0.02633*** |
| Intercept | 2.57754*** | -7.56557*** | -8.04344*** | -2.25295** | -13.48974*** | -14.47046*** | -1.69070** | -11.82697*** | -9.55797*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. The 'yearly' models also include city fixed effects. These are not included in the table for parsimony.*

Table .43: Violent Crime Models: Los Angeles

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | -0.00014 | 0.00041 | -0.00137 | -0.00154 | -0.00134 | -0.00303*** | -0.00240 | -0.00127 | -0.00270 |
| % Residential LU | -0.00900*** | -0.00748*** | -0.00632*** | -0.01233*** | -0.01121*** | -0.00996*** | -0.00884*** | -0.00757*** | -0.00650** |
| % Retail LU | 0.00743*** | 0.00729*** | 0.00703*** | 0.01396*** | 0.01161*** | 0.01154*** | 0.00603* | 0.00582* | 0.00618* |
| % Office LU | -0.00476*** | -0.00358*** | -0.00390*** | -0.00238 | -0.00177** | -0.00195** | -0.01261** | -0.00966* | -0.01005* |
| % School LU | 0.00307* | 0.00331*** | -0.00221* | 0.00445*** | 0.00387*** | 0.00019 | -0.00588 | -0.00513 | -0.01105* |
| # of bars | 0.37920*** | 0.34670*** | 0.35343*** | 0.17418* | 0.13690*** | 0.12911*** | 0.06099 | 0.07555 | 0.04126 |
| # of grocery stores | 0.21353*** | 0.18214*** | 0.19077*** | 0.38427*** | 0.31025*** | 0.31713*** | 0.06559 | 0.08231 | 0.08429 |
| # of restaurants | 0.14147*** | 0.10401*** | 0.08918*** | 0.22677*** | 0.15000*** | 0.13313*** | 0.09731* | 0.08018* | 0.05808 |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00990*** | -0.00979*** | -0.01009*** | -0.00671*** | -0.00649*** | -0.00676*** | -0.00829*** | -0.00878*** | -0.00910*** |
| % Vacant Units | 0.01120*** | 0.01115*** | 0.01089*** | 0.00799*** | 0.00749*** | 0.00704*** | 0.01023 | 0.01142* | 0.01016* |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.54563*** | 0.56507*** | 0.55042*** | 0.44589*** | 0.43410*** | 0.42538*** | 0.66357*** | 0.62880*** | 0.64124*** |
| % Young People | 0.00102 | -0.00215 | 0.00181 | 0.00017 | -0.00204* | 0.00207** | -0.00181 | 0.00071 | 0.00579 |
| Ethnic Heterogeneity | -0.00119 | -0.00088 | -0.00023 | 0.00130 | 0.00167*** | 0.00215*** | -0.00326 | -0.00296 | -0.00309 |
| % Low-income | 0.00061 | 0.00018 | 0.00061 | -0.00053 | -0.00107* | -0.00093* | 0.00667* | 0.00624* | 0.00493* |

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Table .43 – *Continued from previous page*

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.02278*** | 0.02239*** | 0.02418*** | 0.02775*** | 0.02427*** | 0.02686*** | 0.02228** | 0.02236** | 0.02301** |
| % Residential LU | 0.00569* | 0.00371* | 0.00492*** | 0.02016*** | 0.01850*** | 0.02201*** | -0.01036 | -0.00814 | 0.00011 |
| % Retail LU | 0.01862* | 0.00855 | 0.01219 | 0.02701** | 0.02105*** | 0.02268*** | -0.05953 | -0.06050* | -0.06274* |
| % Office LU | -0.02850*** | -0.03173*** | -0.02976*** | -0.01471 | -0.00683 | -0.00358 | -0.02922 | -0.02008 | -0.00462 |
| % School LU | -0.02187* | -0.03211*** | -0.02614*** | -0.00341 | -0.01205* | 0.00113 | -0.04506 | -0.03741 | -0.03852 |
| # of bars | 0.01201*** | 0.01286*** | 0.01202*** | 0.00734*** | 0.00798*** | 0.00688*** | 0.01126* | 0.00880 | 0.00762 |
| # of grocery stores | -0.00187** | -0.00166*** | -0.00042 | -0.00246*** | -0.00181*** | -0.00038 | 0.00016 | -0.00048 | 0.00033 |
| # of restaurants | -0.00170*** | -0.00166*** | -0.00183*** | -0.00071*** | -0.00093*** | -0.00092*** | -0.00201*** | -0.00168** | -0.00167** |
| **Housing** | | | | | | | | | |
| % Homeowners | 0.03604*** | 0.03854*** | 0.03493*** | 0.01565*** | 0.01844*** | 0.01267*** | 0.03538*** | 0.03509*** | 0.03016*** |
| % Vacant Units | 0.17849*** | 0.18942*** | 0.19062*** | 0.10248*** | 0.10242*** | 0.09699*** | 0.08970 | 0.08131 | 0.06929 |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.82768*** | 0.97996*** | 0.88891*** | 0.73544*** | 0.87309*** | 0.55746*** | 1.75731*** | 1.68125*** | 1.32482*** |
| % Young People | -0.04726*** | -0.04858*** | -0.06110*** | -0.01179* | -0.01682*** | -0.03714*** | -0.06286* | -0.07444** | -0.08061** |
| Ethnic Heterogeneity | 0.00320* | 0.00420*** | 0.00354** | -0.00217 | -0.00186 | -0.00228* | 0.00683 | 0.00649 | 0.00390 |
| % Low-income | 0.06380*** | 0.06047*** | 0.05741*** | 0.04362*** | 0.04321*** | 0.04575*** | 0.04896*** | 0.05319*** | 0.06104*** |
| Intercept | -15.51740*** | -28.07809*** | -26.64444*** | -13.66780*** | -25.56885*** | -21.57589*** | -27.82559*** | -37.33454*** | -33.33479*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. The 'yearly' models also include city fixed effects. These are not included in the table for parsimony.*

Table .44: Property Crime Models: Los Angeles

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.00359*** | 0.00251*** | 0.00080* | 0.00655*** | 0.00556*** | 0.00393*** | 0.00489*** | 0.00375*** | 0.00059 |
| % Residential LU | -0.01075*** | -0.01004*** | -0.00848*** | -0.00571*** | -0.00473*** | -0.00319*** | -0.00507*** | -0.00501*** | -0.00327*** |
| % Retail LU | 0.00774*** | 0.00753*** | 0.00739*** | 0.00373*** | 0.00398*** | 0.00410*** | 0.00253*** | 0.00284*** | 0.00050 |
| % Office LU | 0.00237*** | 0.00097** | -0.00007 | -0.00008 | 0.00021 | 0.00010 | -0.00038 | -0.00011 | 0.00045 |
| % School LU | 0.00480*** | 0.00386*** | -0.00182*** | -0.00017 | -0.00032 | -0.00461*** | 0.00686*** | 0.00687*** | 0.00024 |
| # of bars | 0.16588*** | 0.14729*** | 0.13535*** | 0.04816 | 0.03129 | 0.01058 | 0.10456* | 0.08864** | 0.08846** |
| # of grocery stores | 0.23992*** | 0.23583*** | 0.22643*** | 0.05022* | 0.06202*** | 0.06584*** | 0.09719*** | 0.09908*** | 0.13749*** |
| # of restaurants | 0.17102*** | 0.15676*** | 0.13368*** | 0.11902*** | 0.09500*** | 0.07590*** | 0.15189*** | 0.13492*** | 0.13731*** |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00393*** | -0.00272*** | -0.00188*** | -0.00593*** | -0.00545*** | -0.00560*** | 0.00114*** | 0.00147*** | -0.00080*** |
| % Vacant Units | 0.00423*** | 0.00531*** | 0.00551*** | 0.00447*** | 0.00488*** | 0.00418*** | 0.00572*** | 0.00634*** | 0.00442*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.53023*** | 0.53863*** | 0.58359*** | 0.58202*** | 0.60433*** | 0.61248*** | 0.54581*** | 0.56706*** | 0.44619*** |
| % Young People | 0.00120 | 0.00195*** | 0.00500*** | 0.00409*** | 0.00338*** | 0.00452*** | -0.00121 | -0.00114 | -0.00136* |
| Ethnic Heterogeneity | 0.00233*** | 0.00357*** | 0.00359*** | 0.00164*** | 0.00175*** | 0.00252*** | 0.00349*** | 0.00380*** | 0.00397*** |
| % Low-income | -0.00423*** | -0.00359*** | -0.00246*** | -0.00250*** | -0.00266*** | -0.00227*** | -0.00203*** | -0.00140*** | -0.00182*** |

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Table .44 – *Continued from previous page*

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.00600*** | 0.00657*** | 0.00709*** | 0.01363*** | 0.01223*** | 0.01282*** | 0.01670*** | 0.01672*** | 0.01783*** |
| % Residential LU | 0.01725*** | 0.01807*** | 0.01331*** | 0.00192 | 0.00174 | 0.00379*** | 0.02980*** | 0.03012*** | 0.02839*** |
| % Retail LU | -0.00138 | -0.00053 | -0.00413 | 0.00852 | 0.00375 | 0.00280 | -0.00896 | -0.01340*** | -0.00808* |
| % Office LU | 0.01424*** | 0.01655*** | 0.01080*** | -0.01509** | -0.01671*** | -0.01276*** | 0.03578*** | 0.03563*** | 0.04416*** |
| % School LU | -0.00615 | -0.00436 | -0.00116 | -0.02321*** | -0.02332*** | -0.02098*** | -0.03391*** | -0.02936*** | -0.02444*** |
| # of bars | 0.00419*** | 0.00570*** | 0.00603*** | 0.00458*** | 0.00445*** | 0.00410*** | 0.00095 | 0.00126 | -0.00093 |
| # of grocery stores | -0.00072* | -0.00056** | 0.00019 | -0.00177*** | -0.00125*** | -0.00079*** | 0.00019 | 0.00035 | 0.00111*** |
| # of restaurants | -0.00015 | -0.00034*** | -0.00052*** | -0.00128*** | -0.00129*** | -0.00127*** | -0.00057*** | -0.00062*** | -0.00045*** |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.01085*** | -0.01114*** | -0.01065*** | 0.00162 | 0.00200* | 0.00019 | 0.00060 | -0.00103 | -0.00084 |
| % Vacant Units | -0.01115 | -0.00330 | 0.01449*** | -0.04438*** | -0.03880*** | -0.04696*** | 0.05958*** | 0.06083*** | 0.05233*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | -0.49494*** | -0.50059*** | -0.31522*** | 0.57576*** | 0.57670*** | 0.44043*** | -0.35901*** | -0.40169*** | -0.46165*** |
| % Young People | 0.01712*** | 0.01372*** | 0.00515*** | -0.01178*** | -0.01484*** | -0.02080*** | 0.00776** | 0.00461* | 0.01282*** |
| Ethnic Heterogeneity | -0.00082 | -0.00239*** | -0.00084 | -0.00064 | -0.00077 | -0.00154* | 0.00115 | -0.00038 | -0.00169* |
| % Low-income | 0.00868*** | 0.00843*** | -0.00049 | 0.02561*** | 0.02322*** | 0.02595*** | 0.02193*** | 0.02160*** | 0.02089*** |
| Intercept | 4.56860*** | -5.83202*** | -7.85224*** | -8.50670*** | -19.22405*** | -17.60528*** | -0.43799 | -9.45225*** | -8.06921*** |

$*p < .05; **p < .01; ***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. The 'yearly' models also include city fixed effects. These are not included in the table for parsimony.*

Table .45: Violent Crime Models: Oakland

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | -0.00908*** | -0.00815*** | -0.00932*** | -0.00432* | -0.00427** | -0.00585*** | -0.00651 | -0.00774 | -0.00782 |
| % Residential LU | -0.00840*** | -0.00788*** | -0.00600*** | -0.00966*** | -0.00854*** | -0.00682*** | -0.00684* | -0.00605* | -0.00463 |
| % Retail LU | 0.00189 | 0.00108 | 0.00043 | 0.00915*** | 0.00933*** | 0.00842*** | -0.00751 | -0.01017 | -0.01048 |
| % Office LU | 0.01385* | 0.01054** | 0.00717 | 0.00201 | 0.00569 | 0.00339 | 0.03844** | 0.02773** | 0.02554* |
| % School LU | 0.00926 | 0.01219** | 0.01120** | 0.00945 | 0.00887* | 0.00679 | -0.00419 | -0.00079 | -0.00417 |
| # of bars | 0.32383 | 0.33454** | 0.29140* | 0.37046* | 0.32342*** | 0.29784*** | -0.88842 | -0.12667 | -0.16381 |
| # of grocery stores | -0.18352 | -0.20941*** | -0.18658** | -0.03072 | -0.07195 | -0.05600 | 0.14695 | -0.02680 | -0.01456 |
| # of restaurants | 0.09591* | 0.10212*** | 0.09187** | 0.11949** | 0.12738*** | 0.11597*** | 0.21570 | 0.30013** | 0.30580** |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00963*** | -0.00946*** | -0.00961*** | -0.00458*** | -0.00434*** | -0.00520*** | -0.01328** | -0.01197*** | -0.01135** |
| % Vacant Units | 0.00746** | 0.00768*** | 0.00760*** | 0.00877*** | 0.00944*** | 0.00939*** | 0.00288 | 0.00487 | 0.00466 |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.54920*** | 0.58091*** | 0.52849*** | 0.45872*** | 0.45944*** | 0.42103*** | 0.46722*** | 0.41972*** | 0.36575*** |
| % Young People | 0.00048 | 0.00039 | 0.00341* | 0.00121 | 0.00081 | 0.00022 | -0.00679 | -0.00890 | -0.00408 |
| Ethnic Heterogeneity | -0.00117 | -0.00200 | -0.00124 | 0.00070 | 0.00015 | 0.00041 | 0.00245 | 0.00312 | 0.00123 |
| % Low-income | -0.00086 | -0.00048 | 0.00070 | 0.00083 | 0.00112 | 0.00169* | -0.00547 | -0.00947* | -0.00617 |

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Table .45 – *Continued from previous page*

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | -0.01697 | -0.02057* | -0.01404 | 0.00097 | -0.00154 | 0.01037 | 0.00681 | 0.03189 | 0.01212 |
| % Residential LU | -0.01429 | -0.01416 | -0.00702 | 0.00248 | 0.00582 | 0.01774*** | 0.02143 | 0.04649 | 0.00873 |
| % Retail LU | 0.14017*** | 0.11936*** | 0.12450*** | 0.00524 | 0.00497 | 0.00943 | 0.22810* | 0.21142* | 0.17920* |
| % Office LU | -0.01289 | 0.01525 | 0.01705 | -0.24911*** | -0.24977*** | -0.20068*** | -0.06073 | 0.05186 | -0.02097 |
| % School LU | -0.05206 | -0.06422* | -0.04186 | -0.06510 | -0.07195** | -0.04237 | -0.06490 | -0.11301 | -0.11409 |
| # of bars | -0.00210 | -0.00169 | -0.00300 | 0.00338 | 0.00406 | 0.00282 | 0.00282 | -0.00097 | -0.00135 |
| # of grocery stores | -0.00046 | -0.00099 | 0.00014 | -0.00139 | -0.00062 | 0.00005 | -0.00445 | -0.00489 | -0.00561 |
| # of restaurants | -0.00037 | -0.00056 | -0.00082 | 0.00128* | 0.00096* | 0.00086* | -0.00144 | 0.00011 | -0.00063 |
| **Housing** | | | | | | | | | |
| % Homeowners | 0.07939*** | 0.07801*** | 0.06608*** | 0.02199** | 0.01762** | 0.00683 | 0.05256 | 0.06479* | 0.06365* |
| % Vacant Units | 0.34740*** | 0.34310*** | 0.33119*** | 0.15501*** | 0.14750*** | 0.14611*** | 0.37485** | 0.40532*** | 0.44093*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | 1.68827*** | 1.75122*** | 1.37329*** | 1.08437** | 0.85126*** | 0.30485* | 0.65835 | 0.16009 | 1.59237* |
| % Young People | 0.04988** | 0.05530*** | 0.04517*** | -0.00668 | -0.00578 | -0.00387 | 0.10867 | 0.11006* | 0.07805 |
| Ethnic Heterogeneity | 0.02511* | 0.03093*** | 0.02861*** | 0.01661 | 0.01663** | 0.01805** | 0.01749 | 0.03052 | 0.04109 |
| % Low-income | 0.06723*** | 0.06253*** | 0.05880*** | 0.05139*** | 0.04936*** | 0.04723*** | 0.09591* | 0.12020*** | 0.09376*** |
| Intercept | -31.93709*** | -43.72726*** | -38.35497*** | -18.84583*** | -26.70343*** | -20.50203*** | -25.04977 | -34.05611* | -47.61259*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. The 'yearly' models also include city fixed effects. These are not included in the table for parsimony.*

Table .46: Property Crime Models: Oakland

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.00926*** | 0.00732*** | 0.00530*** | 0.01183*** | 0.01048*** | 0.00811*** | 0.00071 | 0.00008 | -0.00126 |
| % Residential LU | -0.00987*** | -0.00950*** | -0.00737*** | -0.00410*** | -0.00416*** | -0.00183*** | -0.00495*** | -0.00563*** | -0.00118* |
| % Retail LU | 0.00665*** | 0.00767*** | 0.00629*** | 0.00536*** | 0.00502*** | 0.00393*** | 0.00274 | 0.00122 | 0.00000 |
| % Office LU | 0.00729 | 0.01206*** | 0.00694*** | 0.00478 | 0.00737** | 0.00134 | 0.00816 | 0.00809** | 0.00049 |
| % School LU | 0.01223* | 0.01090*** | 0.00753*** | 0.00989 | 0.00542* | 0.00296 | 0.01067 | 0.00655* | 0.00984*** |
| # of bars | 0.11095 | 0.15824** | 0.15170** | 0.26478* | 0.23413*** | 0.19660** | 0.19844 | 0.18315* | 0.15611* |
| # of grocery stores | 0.01532 | -0.02350 | -0.02247 | -0.16682** | -0.13724*** | -0.12368*** | -0.12608 | -0.11851** | -0.08032* |
| # of restaurants | 0.15403*** | 0.16633*** | 0.15493*** | 0.07766** | 0.06890*** | 0.05813*** | 0.08729** | 0.10916*** | 0.12603*** |
| **Housing** | | | | | | | | | |
| % Homeowners | 0.00038 | 0.00041 | 0.00014 | 0.00069 | 0.00098* | 0.00007 | 0.00170 | 0.00200*** | 0.00034 |
| % Vacant Units | 0.00299 | 0.00388*** | 0.00395*** | 0.00318 | 0.00293** | 0.00289** | 0.00365 | 0.00485*** | 0.00504*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.53880*** | 0.55196*** | 0.51683*** | 0.53098*** | 0.57516*** | 0.53156*** | 0.56288*** | 0.60443*** | 0.46045*** |
| % Young People | -0.00169 | -0.00232* | 0.00073 | 0.00124 | 0.00057 | 0.00241* | 0.00023 | 0.00029 | -0.00083 |
| Ethnic Heterogeneity | -0.00086 | -0.00013 | 0.00027 | 0.00085 | 0.00056 | 0.00074 | 0.00345** | 0.00377*** | 0.00348*** |
| % Low-income | -0.00302** | -0.00268*** | -0.00149** | -0.00146 | -0.00056 | -0.00072 | 0.00134 | 0.00247*** | 0.00180** |

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Table .46 – *Continued from previous page*

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | -0.01206 | -0.01184** | -0.00729 | 0.02142** | 0.01632*** | 0.02810*** | 0.00373 | 0.00291 | 0.00478 |
| % Residential LU | -0.00103 | -0.00071 | 0.00574** | -0.01121 | -0.01375*** | 0.00938*** | 0.00677 | 0.00507 | 0.02457*** |
| % Retail LU | 0.02848 | 0.02382* | 0.02038 | -0.11990*** | -0.12047*** | -0.10905*** | -0.00114 | 0.00307 | 0.03580* |
| % Office LU | 0.09064 | 0.04403 | 0.04458 | -0.20206*** | -0.19356*** | -0.15168*** | -0.04483 | -0.06705* | 0.02228 |
| % School LU | 0.13332*** | 0.09755*** | 0.10658*** | -0.01868 | -0.03177* | -0.02003 | 0.05236* | 0.04168** | 0.05192*** |
| # of bars | 0.00857** | 0.00844*** | 0.00842*** | -0.00046 | -0.00204 | -0.00115 | -0.00319 | -0.00328 | -0.00234 |
| # of grocery stores | -0.00329** | -0.00335*** | -0.00314*** | -0.00095 | -0.00145* | -0.00136* | 0.00016 | -0.00090 | -0.00346*** |
| # of restaurants | 0.00080 | 0.00065** | 0.00074** | 0.00136** | 0.00107*** | 0.00120*** | 0.00093 | 0.00081* | 0.00123*** |
| **Housing** | | | | | | | | | |
| % Homeowners | 0.02111*** | 0.01820*** | 0.01340*** | 0.02873*** | 0.02527*** | 0.01802*** | 0.02929*** | 0.02552*** | 0.00990* |
| % Vacant Units | 0.04574 | 0.04505** | 0.04834*** | 0.17829*** | 0.18431*** | 0.16459*** | 0.20520*** | 0.20674*** | 0.14377*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.35025 | 0.30786** | -0.00401 | 1.29350*** | 1.44482*** | 0.51670*** | 0.07924 | 0.15690 | -0.71162*** |
| % Young People | -0.01036 | -0.00863 | -0.00706 | -0.03033*** | -0.03179*** | -0.01371** | 0.01967* | 0.01733** | 0.02516*** |
| Ethnic Heterogeneity | -0.00880 | -0.00538 | -0.00311 | 0.00128 | 0.00339 | 0.00508 | 0.01780** | 0.01759*** | 0.00731 |
| % Low-income | 0.01089 | 0.00710 | 0.00644 | 0.02014* | 0.01034* | 0.02747*** | -0.01697 | -0.02270*** | 0.01128** |
| Intercept | -5.52962** | -15.39479*** | -12.09857*** | -18.18242*** | -29.96014*** | -20.81542*** | -7.29016*** | -17.41278*** | -6.91661*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. The 'yearly' models also include city fixed effects. These are not included in the table for parsimony.*

Table .47: Violent Crime Models: Sacramento

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.00075 | -0.00062 | -0.00460 | -0.00237 | -0.00363 | -0.00645** | -0.01224 | -0.01539 | -0.01483 |
| % Residential LU | -0.01249*** | -0.01133*** | -0.01015*** | -0.01975*** | -0.01795*** | -0.01628*** | -0.01010* | -0.01427*** | -0.01364*** |
| % Retail LU | 0.00930*** | 0.00911*** | 0.00698*** | 0.01983*** | 0.01796*** | 0.01645*** | -0.00330 | -0.00418 | -0.00421 |
| % Office LU | -0.00033 | 0.00062 | -0.00550 | 0.01085** | 0.00959*** | 0.00510* | -0.04844 | -0.04954 | -0.05151 |
| % School LU | 0.00098 | 0.00115 | -0.00437* | -0.00017 | 0.00063 | -0.00274 | -0.00071 | -0.00640 | -0.01372 |
| # of bars | 0.74832*** | 0.25138 | 0.20664 | 0.56847** | 0.07674 | 0.01276 | -0.59058 | -0.74123 | -0.72588 |
| # of grocery stores | 0.43328*** | 0.40661*** | 0.44246*** | 0.84995*** | 0.80754*** | 0.83401*** | 0.38200 | 0.21147 | 0.18753 |
| # of restaurants | 0.04397 | 0.02575 | 0.01613 | 0.16972*** | 0.07530*** | 0.06857*** | 0.10358 | 0.09866 | 0.08040 |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00724*** | -0.00642*** | -0.00754*** | -0.00615*** | -0.00465*** | -0.00564*** | -0.01400* | -0.01243* | -0.01117* |
| % Vacant Units | 0.01152*** | 0.00972*** | 0.00920*** | 0.00765* | 0.00482* | 0.00412* | 0.02154 | 0.01374 | 0.01384 |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.67487*** | 0.66190*** | 0.57745*** | 0.64364*** | 0.58788*** | 0.50606*** | 0.56701*** | 0.49871*** | 0.51757*** |
| % Young People | 0.00617* | 0.00454* | 0.00537** | 0.00567* | 0.00504** | 0.00728*** | -0.00206 | -0.00038 | 0.00139 |
| Ethnic Heterogeneity | 0.00602** | 0.00767*** | 0.01094*** | -0.00355 | -0.00286 | 0.00176 | 0.01182 | 0.00789 | 0.01512 |
| % Low-income | 0.00339 | 0.00343* | 0.00314* | 0.00429* | 0.00322* | 0.00286* | 0.00422 | 0.00128 | 0.00407 |

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Table .47 – *Continued from previous page*

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | -0.00167 | -0.00037 | -0.00841 | 0.00754 | 0.00960 | -0.00118 | 0.00456 | 0.00206 | 0.00971 |
| % Residential LU | 0.00255 | 0.00018 | 0.00097 | 0.01470** | 0.01872*** | 0.01762*** | 0.02890 | 0.02075 | 0.01536 |
| % Retail LU | 0.02940 | 0.01837 | 0.03059 | 0.08367** | 0.06746*** | 0.06629*** | 0.02586 | 0.03813 | 0.01058 |
| % Office LU | -0.02237 | -0.00822 | -0.02167 | -0.07431* | -0.02970 | -0.03115 | 0.02503 | 0.06056 | 0.08533 |
| % School LU | -0.01888 | -0.01582 | 0.00285 | 0.06025 | 0.05641** | 0.07746*** | 0.24997* | 0.24447* | 0.24327* |
| # of bars | -0.00071 | 0.00210 | 0.00034 | -0.01035* | -0.00826** | -0.00833** | 0.04090* | 0.02495 | 0.02788 |
| # of grocery stores | 0.00042 | 0.00177 | 0.00517 | -0.00576 | -0.00386 | -0.00109 | -0.00938 | -0.01469 | -0.01746 |
| # of restaurants | -0.00043 | -0.00109 | -0.00100 | 0.00244* | 0.00238** | 0.00256*** | -0.00576 | -0.00082 | -0.00116 |
| **Housing** | | | | | | | | | |
| % Homeowners | 0.00905 | 0.01282 | 0.00764 | -0.02839* | -0.01515* | -0.01770** | -0.00678 | 0.02209 | 0.02407 |
| % Vacant Units | 0.10563** | 0.13915*** | 0.09556*** | 0.01052 | -0.00423 | -0.05793* | -0.03556 | 0.00541 | 0.04618 |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.62250* | 0.73982** | 0.29989** | 0.47501 | 0.37310 | -0.09692 | -1.50267 | -1.34741 | -0.71547 |
| % Young People | 0.01718 | 0.01383 | 0.01586 | 0.02909 | 0.02508 | 0.02315 | 0.11441 | 0.05073 | 0.04402 |
| Ethnic Heterogeneity | 0.04132*** | 0.03895*** | 0.04266*** | 0.05575*** | 0.05332*** | 0.04885*** | 0.03556 | 0.05925 | 0.03771 |
| % Low-income | 0.03398** | 0.02866*** | 0.03381*** | -0.00273 | 0.00930 | 0.02348*** | 0.07409 | 0.07422 | 0.07370* |
| Intercept | -16.05248*** | -28.07826*** | -22.83919*** | -11.94811*** | -22.11141*** | -16.23697*** | 2.07712 | -11.35239 | -17.23788* |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. The 'yearly' models also include city fixed effects. These are not included in the table for parsimony.*

Table .48: Property Crime Models: Sacramento

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.00638** | 0.00497*** | 0.00039 | 0.01660*** | 0.01533*** | 0.00989*** | 0.01356*** | 0.01270*** | 0.00703*** |
| % Residential LU | -0.01051*** | -0.00966*** | -0.00817*** | -0.00620*** | -0.00452*** | -0.00407*** | -0.01118*** | -0.00926*** | -0.00779*** |
| % Retail LU | 0.01827*** | 0.02095*** | 0.01885*** | 0.00942*** | 0.00922*** | 0.00703*** | 0.00627*** | 0.00727*** | 0.00515*** |
| % Office LU | 0.00526* | 0.00285* | -0.00234 | 0.00777** | 0.00803*** | 0.00215 | 0.01555*** | 0.01531*** | 0.01002*** |
| % School LU | 0.00546** | 0.00582*** | -0.00009 | 0.00045 | 0.00151 | -0.00408** | -0.00197 | -0.00063 | -0.00493*** |
| # of bars | 0.32393** | 0.19333** | 0.14155* | 0.11443 | 0.12645 | 0.05968 | 0.30238** | 0.23784*** | 0.19798*** |
| # of grocery stores | 0.43489*** | 0.50639*** | 0.55169*** | 0.20901** | 0.19265*** | 0.23854*** | 0.08083 | 0.13674*** | 0.19431*** |
| # of restaurants | 0.21142*** | 0.17055*** | 0.16757*** | 0.07997*** | 0.07692*** | 0.05492*** | 0.18005*** | 0.14048*** | 0.14831*** |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00389*** | -0.00351*** | -0.00338*** | -0.00803*** | -0.00728*** | -0.00764*** | -0.00376*** | -0.00379*** | -0.00459*** |
| % Vacant Units | 0.00358* | 0.00136 | 0.00134 | 0.00582** | 0.00566*** | 0.00531*** | 0.00778*** | 0.00752*** | 0.00691*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.66348*** | 0.62801*** | 0.57472*** | 0.72642*** | 0.74535*** | 0.69008*** | 0.67006*** | 0.65272*** | 0.54858*** |
| % Young People | -0.00276* | -0.00255** | 0.00226** | 0.00853*** | 0.01024*** | 0.01279*** | -0.00118 | -0.00020 | 0.00250*** |
| Ethnic Heterogeneity | -0.00300* | -0.00423*** | -0.00320*** | 0.00120 | 0.00219* | 0.00423*** | -0.00087 | -0.00151* | -0.00056 |
| % Low-income | 0.00127 | 0.00109 | 0.00141* | -0.00089 | -0.00042 | 0.00001 | -0.00279** | -0.00251*** | -0.00150** |

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Table .48 – *Continued from previous page*

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.00333 | 0.00077 | 0.00339 | 0.01325* | 0.00611 | 0.01397*** | 0.00409 | 0.00024 | -0.00118 |
| % Residential LU | 0.01131*** | 0.01461*** | 0.01146*** | 0.01255*** | 0.01484*** | 0.01041*** | 0.01171*** | 0.01456*** | 0.01179*** |
| % Retail LU | 0.00240 | -0.00043 | -0.00656 | 0.00536 | 0.03461** | 0.02627* | 0.01256 | 0.04012*** | 0.03244*** |
| % Office LU | 0.02190 | 0.04831*** | 0.06775*** | -0.04874** | -0.01979 | -0.00169 | 0.00854 | 0.03805*** | 0.04656*** |
| % School LU | -0.00644 | -0.00459 | -0.00946 | -0.00602 | -0.00979 | -0.03276** | 0.02886 | 0.01692 | 0.02131* |
| # of bars | -0.01174*** | -0.01448*** | -0.01328*** | 0.00074 | 0.00223 | 0.00278 | -0.00345 | -0.00534*** | -0.00525*** |
| # of grocery stores | -0.00194 | -0.00392** | -0.00354* | -0.01238*** | -0.01094*** | -0.01009*** | -0.00717*** | -0.00690*** | -0.00606*** |
| # of restaurants | 0.00421*** | 0.00507*** | 0.00456*** | 0.00212** | 0.00148** | 0.00053 | 0.00209*** | 0.00223*** | 0.00244*** |
| **Housing** | | | | | | | | | |
| % Homeowners | 0.00174 | 0.01066** | 0.00540 | 0.00058 | 0.00945* | 0.00246 | 0.00730 | 0.01634*** | 0.01024*** |
| % Vacant Units | -0.00630 | 0.00870 | 0.01280 | -0.07639** | -0.05135** | -0.03518* | 0.00824 | 0.03625** | -0.02134 |
| **Time Varying** | | | | | | | | | |
| Logged Population | -0.58761*** | -0.64923*** | -0.41567*** | -0.18600 | -0.30247** | 0.16966** | -0.16767 | -0.24444** | -0.37217*** |
| % Young People | 0.02763* | 0.04323*** | 0.00951 | 0.08647*** | 0.09288*** | 0.04910*** | 0.05997*** | 0.07665*** | 0.04693*** |
| Ethnic Heterogeneity | 0.01673*** | 0.02243*** | 0.01802*** | 0.02214*** | 0.02229*** | 0.01876*** | 0.00572 | 0.01527*** | 0.00989*** |
| % Low-income | 0.01070 | 0.01230*** | 0.01011*** | 0.03910*** | 0.03641*** | 0.02777*** | 0.00525 | -0.00223 | 0.00785** |
| Intercept | 2.53555 | -8.26707*** | -9.16178*** | -4.56489** | -15.31550*** | -18.26029*** | -1.94645 | -13.07849*** | -9.38047*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. The 'yearly' models also include city fixed effects. These are not included in the table for parsimony.*

Table .49: Violent Crime Models: San Jose

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.00869** | 0.00837*** | 0.00460* | 0.01005** | 0.00961*** | 0.00561* | 0.00295 | 0.00504 | 0.00285 |
| % Residential LU | -0.00498*** | -0.00344*** | -0.00268** | -0.00675*** | -0.00630*** | -0.00528*** | -0.01325* | -0.01362* | -0.01335* |
| % Retail LU | 0.01244*** | 0.01286*** | 0.01184*** | 0.02545*** | 0.02081*** | 0.02042*** | 0.00417 | 0.00251 | 0.00104 |
| % Office LU | 0.02176*** | 0.02111*** | 0.01703*** | 0.02832*** | 0.02533*** | 0.02273*** | 0.03099** | 0.02742** | 0.02428* |
| % School LU | 0.00885 | 0.01214** | 0.00663 | 0.01751* | 0.01330** | 0.01027* | 0.02009 | 0.01791 | 0.01024 |
| # of bars | 0.35280* | 0.35029*** | 0.31467*** | 0.26628 | 0.13635 | 0.07232 | -0.20837 | -0.20252 | -0.23447 |
| # of grocery stores | 0.24346** | 0.18869*** | 0.20438*** | 0.46885*** | 0.38905*** | 0.40235*** | -0.78621 | -0.72644 | -0.73401 |
| # of restaurants | 0.07465** | 0.06152*** | 0.05113** | 0.10678** | 0.12613*** | 0.10485*** | 0.13017 | 0.11465 | 0.11441 |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00921*** | -0.00795*** | -0.00815*** | -0.01095*** | -0.00964*** | -0.00921*** | -0.00589 | -0.00621 | -0.00712 |
| % Vacant Units | 0.01008** | 0.01417*** | 0.01252*** | 0.01288** | 0.01047** | 0.00818* | -0.01363 | -0.01545 | -0.01516 |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.57235*** | 0.56881*** | 0.52600*** | 0.53776*** | 0.49144*** | 0.46564*** | 0.48059*** | 0.41110*** | 0.34596** |
| % Young People | 0.00482 | -0.00069 | 0.00323 | -0.00888 | -0.00879** | -0.00114 | 0.02088 | 0.02393* | 0.02329* |
| Ethnic Heterogeneity | -0.00673*** | -0.00507*** | -0.00287* | -0.00300 | -0.00043 | 0.00218 | -0.01079 | -0.00813 | -0.00270 |
| % Low-income | 0.00298 | 0.00151 | 0.00167 | 0.00030 | -0.00045 | 0.00062 | -0.00593 | -0.00458 | -0.00557 |

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Table .49 – *Continued from previous page*

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | -0.02763*** | -0.03494*** | -0.02889*** | -0.01301 | -0.01619* | -0.00838 | -0.04054 | -0.03902 | -0.03570 |
| % Residential LU | -0.00499 | -0.01390*** | -0.01308*** | -0.00603 | -0.01085 | -0.00384 | -0.01525 | -0.01576 | -0.02166 |
| % Retail LU | 0.02674 | 0.03426** | 0.02665* | 0.02293 | 0.02583 | 0.01943 | 0.16885* | 0.17371* | 0.17390* |
| % Office LU | 0.03070 | 0.02657 | 0.01025 | 0.01186 | 0.02756 | -0.00362 | -0.08725 | -0.07082 | -0.09718 |
| % School LU | -0.32130*** | -0.25249*** | -0.23767*** | -0.39400*** | -0.31656*** | -0.25062*** | 0.55407* | 0.53161* | 0.56595* |
| # of bars | -0.00989 | -0.00850* | -0.00695 | -0.02628** | -0.02384*** | -0.02623*** | -0.01828 | -0.01683 | -0.01361 |
| # of grocery stores | -0.00556 | -0.00852*** | -0.00694** | -0.00487 | -0.00592 | -0.00461 | 0.01063 | 0.01078 | 0.01243 |
| # of restaurants | 0.00059 | 0.00138* | 0.00131* | 0.00170 | 0.00093 | 0.00152 | -0.00647 | -0.00685 | -0.00700 |
| **Housing** | | | | | | | | | |
| % Homeowners | 0.00156 | 0.00207 | -0.00102 | 0.01270 | 0.01734* | 0.01371* | 0.01443 | 0.01495 | 0.00653 |
| % Vacant Units | -0.14425** | -0.10788*** | -0.09318** | -0.01472 | 0.03490 | 0.03694 | -0.34420 | -0.34882 | -0.30348 |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.17467 | 0.33944* | 0.23540* | 0.71491* | 1.01919*** | 0.41502** | -0.18160 | -0.14697 | -0.01790 |
| % Young People | 0.09664*** | 0.04455*** | 0.02197* | 0.11957*** | 0.08472*** | 0.06269*** | -0.02643 | -0.03912 | -0.08720 |
| Ethnic Heterogeneity | 0.01012 | 0.00344 | 0.00138 | 0.01428 | 0.00890 | 0.00473 | -0.00827 | -0.01123 | -0.02121 |
| % Low-income | 0.05231*** | 0.07083*** | 0.07782*** | 0.01643 | 0.02768 | 0.04903*** | 0.15183 | 0.15307* | 0.15506** |
| Intercept | -6.77301*** | -17.71843*** | -16.10839*** | -14.85414*** | -28.19327*** | -21.46996*** | -3.43283 | -14.85227** | -14.61178* |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. The 'yearly' models also include city fixed effects. These are not included in the table for parsimony.*

Table .50: Property Crime Models: San Jose

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.01628*** | 0.01455*** | 0.01027*** | 0.01689*** | 0.01363*** | 0.00703*** | 0.01743*** | 0.01394*** | 0.00725*** |
| % Residential LU | -0.00815*** | -0.00781*** | -0.00609*** | -0.00344*** | -0.00177** | -0.00059 | -0.00593*** | -0.00425*** | -0.00270*** |
| % Retail LU | 0.01691*** | 0.01828*** | 0.01718*** | 0.01146*** | 0.01017*** | 0.00831*** | 0.00913*** | 0.00851*** | 0.00662*** |
| % Office LU | 0.01882*** | 0.01836*** | 0.01394*** | 0.01415*** | 0.01245*** | 0.00581*** | 0.01393*** | 0.01244*** | 0.00541*** |
| % School LU | 0.01146* | 0.01059*** | 0.00566* | 0.00823 | 0.00540 | -0.00587 | 0.01053** | 0.01036*** | 0.00292 |
| # of bars | 0.09068 | -0.04936 | -0.13382* | 0.06768 | 0.19398** | 0.12395 | 0.07857 | 0.06511 | -0.02357 |
| # of grocery stores | 0.14086 | 0.08756* | 0.09400** | 0.15137* | 0.15125*** | 0.18301*** | 0.05645 | 0.07716** | 0.08105** |
| # of restaurants | 0.19601*** | 0.19954*** | 0.20153*** | 0.06402** | 0.04896*** | 0.04691*** | 0.11751*** | 0.09940*** | 0.10638*** |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00559*** | -0.00476*** | -0.00476*** | -0.00852*** | -0.00681*** | -0.00819*** | -0.00219*** | -0.00211*** | -0.00322*** |
| % Vacant Units | 0.01180*** | 0.01731*** | 0.01649*** | 0.01503*** | 0.01983*** | 0.01749*** | 0.00687*** | 0.01035*** | 0.00831*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.49409*** | 0.51876*** | 0.49727*** | 0.66760*** | 0.69040*** | 0.56773*** | 0.63163*** | 0.63510*** | 0.53923*** |
| % Young People | 0.00393 | -0.00223 | 0.00145 | 0.00477* | 0.00012 | 0.00078 | -0.00148 | -0.00176 | -0.00208** |
| Ethnic Heterogeneity | -0.00182 | 0.00193** | 0.00413*** | -0.00071 | -0.00010 | 0.00311*** | 0.00031 | 0.00177** | 0.00368*** |
| % Low-income | -0.00001 | -0.00111 | 0.00002 | 0.00101 | -0.00162* | 0.00020 | -0.00144 | -0.00190** | -0.00196*** |

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Table .50 – *Continued from previous page*

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | -0.01425*** | -0.02233*** | -0.01775*** | -0.02903*** | -0.02968*** | -0.02280*** | -0.00519 | -0.00416* | -0.00132 |
| % Residential LU | 0.00001 | -0.00544** | -0.00521*** | -0.03244*** | -0.03572*** | -0.02683*** | -0.00036 | -0.00339** | 0.00136 |
| % Retail LU | 0.08839*** | 0.10171*** | 0.09369*** | 0.01879 | 0.02982*** | 0.02425*** | -0.01684* | -0.00504 | -0.01095* |
| % Office LU | -0.00242 | 0.00798 | 0.00340 | -0.00974 | -0.00584 | -0.06120*** | 0.01793 | 0.01215 | 0.01210 |
| % School LU | -0.16444*** | -0.16883*** | -0.13774*** | -0.10753* | -0.05353 | -0.07414** | -0.15351*** | -0.15351*** | -0.12334*** |
| # of bars | -0.01204** | -0.01669*** | -0.01443*** | -0.02591*** | -0.02625*** | -0.02503*** | 0.00362 | -0.00050 | -0.00384 |
| # of grocery stores | -0.00893*** | -0.01193*** | -0.01044*** | 0.00343 | 0.00245 | 0.00549*** | -0.00562** | -0.00450*** | -0.00409*** |
| # of restaurants | 0.00083 | 0.00244*** | 0.00255*** | 0.00030 | 0.00048 | 0.00031 | 0.00190*** | 0.00191*** | 0.00265*** |
| **Housing** | | | | | | | | | |
| % Homeowners | 0.00065 | 0.00260 | 0.00200 | -0.00789 | -0.00899*** | -0.01675*** | -0.00520 | -0.00555** | -0.00542** |
| % Vacant Units | 0.02605 | 0.03921* | 0.04108* | -0.27216*** | -0.27753*** | -0.30974*** | -0.04783* | -0.04241** | -0.09478*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | -0.01371 | -0.08408 | -0.18308*** | 1.21101*** | 1.26937*** | 0.79525*** | 0.43075*** | 0.37840*** | -0.00845 |
| % Young People | 0.05379*** | 0.03868*** | 0.02540*** | 0.04483*** | 0.00215 | 0.00669 | 0.04131*** | 0.02721*** | 0.02974*** |
| Ethnic Heterogeneity | 0.01366*** | 0.00671** | 0.00291 | 0.00465 | 0.00674** | 0.00514* | 0.01280*** | 0.01174*** | 0.01086*** |
| % Low-income | -0.00284 | 0.01684** | 0.02068*** | 0.04482*** | 0.05967*** | 0.06033*** | -0.02481*** | -0.01826*** | 0.00089 |
| Intercept | -2.72837** | -11.40388*** | -10.01750*** | -14.22089*** | -24.10970*** | -18.06655*** | -6.95820*** | -15.94971*** | -11.38948*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. The 'yearly' models also include city fixed effects. These are not included in the table for parsimony.*

Table .51: Violent Crime Models: Scottsdale

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.03025 | 0.01248 | 0.01262 | 0.01458 | -0.00365 | -0.00472 | 0.06441 | 0.03714 | 0.02349 |
| % Residential LU | -0.00882*** | -0.00927*** | -0.00856*** | -0.01816*** | -0.01927*** | -0.01685*** | 0.00385 | 0.00668 | 0.00971 |
| % Retail LU | -0.00026 | 0.00015 | -0.00186 | 0.01469* | 0.01044** | 0.00862* | 0.02573 | 0.02441 | 0.02546 |
| % Office LU | -0.01031 | -0.01451 | -0.01980 | 0.03179** | 0.02031* | 0.01212 | 0.03900 | 0.03454 | 0.04161 |
| % School LU | -0.02590 | -0.02537 | -0.02766 | -0.00283 | -0.00395 | -0.00808 | 0.06299** | 0.06106** | 0.04773* |
| # of bars | 0.27346 | 0.31878 | 0.35911 | -0.78713 | -0.70054* | -0.64968* | 1.14455 | 1.12727 | 1.02473 |
| # of grocery stores | 0.27421 | 0.31846 | 0.38470* | 0.49661 | 0.45131** | 0.55217** | -1.02553 | -1.01805 | -0.67943 |
| # of restaurants | 0.25424** | 0.18629** | 0.16341** | 0.49972*** | 0.41844*** | 0.38760*** | 0.22854 | 0.22321 | 0.11841 |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00410 | -0.00486 | -0.00565* | -0.00895* | -0.00633* | -0.00363 | 0.02238 | 0.01652 | 0.00337 |
| % Vacant Units | 0.00139 | 0.00445 | 0.00520 | 0.00308 | 0.00720 | 0.00823 | -0.00798 | -0.00670 | -0.00840 |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.59968*** | 0.57153*** | 0.49709*** | 0.62175*** | 0.60348*** | 0.58860*** | 0.78998* | 0.84236** | 0.30839 |
| % Young People | -0.00140 | -0.00069 | 0.00011 | -0.02114* | -0.01634* | -0.00924 | 0.05798* | 0.05691* | 0.03602* |
| Ethnic Heterogeneity | -0.00217 | -0.00372 | -0.00447 | -0.01036 | -0.00899 | -0.00403 | -0.01930 | -0.01686 | -0.01592 |
| % Low-income | 0.00989 | 0.00675 | 0.00966* | 0.00910 | 0.00505 | 0.00851 | -0.00432 | -0.00938 | 0.00813 |

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Table .51 – *Continued from previous page*

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.08435 | 0.06935 | 0.10225* | -0.23819* | -0.26338** | -0.19769** | 0.57319 | 0.50173 | 0.01971 |
| % Residential LU | 0.00178 | 0.00082 | 0.00162 | -0.00033 | -0.00185 | 0.00117 | -0.01433 | -0.01516 | -0.00844 |
| % Retail LU | 0.01849 | 0.01859 | 0.03049 | 0.01082 | 0.05134 | 0.09746* | 0.00768 | 0.02014 | 0.11973 |
| % Office LU | 0.07230 | 0.07810 | 0.09071 | 0.05016 | -0.00488 | 0.05866 | 0.01350 | 0.03688 | -0.13814 |
| % School LU | -0.06950 | -0.07067 | -0.07970 | 0.00470 | 0.01354 | -0.01447 | -0.00592 | 0.01109 | -0.07078 |
| # of bars | 0.01224 | 0.00407 | 0.00277 | 0.00249 | -0.00148 | -0.00096 | -0.21334* | -0.20569* | -0.19197** |
| # of grocery stores | 0.00178 | -0.00038 | -0.00094 | 0.05923** | 0.05427*** | 0.06099*** | -0.07211 | -0.06637 | -0.00767 |
| # of restaurants | 0.00736 | 0.00834** | 0.00787* | -0.00215 | -0.00376 | -0.00383 | 0.04390* | 0.04423* | 0.03307* |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.01989 | -0.01522 | -0.01705 | 0.01280 | 0.01424 | -0.02030 | 0.00664 | -0.00327 | 0.03131 |
| % Vacant Units | -0.03747 | -0.03936 | -0.03554 | 0.02914 | 0.03575 | -0.01108 | 0.32161* | 0.30946* | 0.23299* |
| **Time Varying** | | | | | | | | | |
| Logged Population | -0.67970* | -0.61687* | -0.61027** | 0.73207 | 0.88966 | 0.08058 | 2.23798 | 1.94993 | 1.25737 |
| % Young People | 0.11220* | 0.10043* | 0.07978* | 0.09887 | 0.11415* | 0.02017 | 0.31988 | 0.24449 | 0.17625 |
| Ethnic Heterogeneity | -0.05033 | -0.03795 | -0.00590 | 0.00584 | 0.00048 | 0.03537 | -0.02230 | 0.04839 | 0.20335 |
| % Low-income | 0.00519 | 0.02552 | -0.03229 | 0.07751 | 0.10052 | 0.02367 | -0.40405 | -0.43901 | -0.44722* |
| Intercept | 3.05600 | -8.35868* | -7.87032** | -16.28999* | -28.73949*** | -16.98041*** | -41.04981 | -46.96442* | -40.12115* |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. The 'yearly' models also include city fixed effects. These are not included in the table for parsimony.*

Table .52: Property Crime Models: Scottsdale

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.02566 | 0.00382 | 0.00492 | 0.02620 | 0.00942 | 0.01401 | 0.03197** | 0.01801*** | 0.02058*** |
| % Residential LU | -0.00980*** | -0.01066*** | -0.00904*** | -0.00097 | -0.00181 | 0.00123 | -0.00408*** | -0.00416*** | -0.00272*** |
| % Retail LU | 0.02239*** | 0.02188*** | 0.01894*** | 0.01403** | 0.01210*** | 0.00848** | 0.01119*** | 0.01161*** | 0.00756*** |
| % Office LU | 0.02598** | 0.01931*** | 0.01056*** | -0.00074 | -0.00732 | -0.01860* | 0.01164* | 0.00820*** | -0.00018 |
| % School LU | 0.01347 | 0.00620* | -0.00071 | 0.00118 | -0.00093 | -0.00958 | 0.00680 | 0.00544* | -0.00147 |
| # of bars | -0.06778 | -0.05245 | -0.00166 | 0.40406 | 0.37655* | 0.39418* | 0.37757* | 0.44036*** | 0.45636*** |
| # of grocery stores | 0.69506*** | 0.69344*** | 0.72068*** | 0.45618* | 0.35636** | 0.53993*** | 0.21286 | 0.18305*** | 0.29758*** |
| # of restaurants | 0.56493*** | 0.33554*** | 0.31554*** | 0.18295* | 0.15024** | 0.13081* | 0.29468*** | 0.16741*** | 0.16437*** |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00281 | -0.00146 | -0.00216** | -0.00208 | -0.00151 | -0.00409* | 0.00254 | 0.00328*** | 0.00133 |
| % Vacant Units | 0.00891*** | 0.01118*** | 0.01207*** | 0.01458** | 0.01751*** | 0.01684*** | 0.00060 | -0.00113 | -0.00065 |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.59808*** | 0.63325*** | 0.56100*** | 0.74128*** | 0.73350*** | 0.64137*** | 0.73205*** | 0.76511*** | 0.64484*** |
| % Young People | 0.00847** | 0.00472** | 0.00341** | -0.00394 | -0.00420 | -0.00275 | 0.00697** | 0.00809*** | 0.00506*** |
| Ethnic Heterogeneity | -0.00230 | -0.00111 | -0.00260* | 0.00566 | 0.00587 | -0.00100 | -0.00476** | -0.00448*** | -0.00638*** |
| % Low-income | 0.01187** | 0.00685*** | 0.00184 | 0.00106 | -0.00172 | -0.00245 | 0.00442 | 0.00019 | -0.00017 |

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Table .52 – *Continued from previous page*

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.00700 | -0.01080 | -0.01088 | 0.00507 | -0.00188 | -0.01904 | 0.08044** | 0.05371*** | 0.04220** |
| % Residential LU | 0.00321 | 0.00358*** | 0.00596*** | -0.00486 | -0.00468 | -0.00266 | 0.00135 | 0.00041 | 0.00168* |
| % Retail LU | -0.01763 | -0.00646 | -0.00363 | -0.00990 | -0.00128 | 0.02761 | -0.02009 | -0.00251 | -0.00162 |
| % Office LU | 0.09898* | 0.10387*** | 0.09882*** | 0.15317* | 0.13676* | 0.13316* | 0.03522 | 0.02637 | 0.02273 |
| % School LU | -0.01479 | -0.01792 | -0.02207* | 0.02444 | 0.02834 | 0.00160 | 0.00764 | 0.02503** | 0.01197 |
| # of bars | -0.01334 | -0.01184** | -0.00778* | 0.00312 | 0.00436 | 0.00644 | -0.00150 | -0.00115 | 0.00061 |
| # of grocery stores | 0.03557*** | 0.02645*** | 0.03283*** | -0.00946 | -0.00791 | 0.00292 | -0.00256 | -0.00571 | 0.00047 |
| # of restaurants | 0.00786*** | 0.00692*** | 0.00526*** | 0.00691* | 0.00592* | 0.00333 | 0.00677*** | 0.00663*** | 0.00537*** |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00073 | -0.00324 | -0.00747* | -0.01879 | -0.01840 | -0.03475*** | -0.00852 | -0.00922* | -0.01400*** |
| % Vacant Units | 0.01754 | 0.02591*** | 0.00493 | -0.02625 | -0.03216 | -0.05788*** | -0.00345 | -0.00238 | -0.01797*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | -0.25814 | -0.23749** | -0.52476*** | -0.20158 | -0.10912 | -0.45426* | -0.15361 | -0.16060** | -0.31426*** |
| % Young People | 0.10485*** | 0.11002*** | 0.12652*** | 0.05425 | 0.04589 | 0.01782 | 0.03661* | 0.03228** | 0.03538*** |
| Ethnic Heterogeneity | -0.01208 | -0.00214 | -0.01173 | 0.02105 | 0.01506 | 0.01298 | 0.00395 | -0.00115 | -0.00525 |
| % Low-income | -0.05157* | -0.04444*** | -0.02141* | -0.04829 | -0.02789 | -0.01673 | -0.04247* | -0.02211* | -0.01316 |
| Intercept | -1.34719 | -11.58491*** | -7.93904*** | -2.95590 | -13.43568*** | -7.19646** | -1.00013 | -10.79788*** | -7.68093*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. The 'yearly' models also include city fixed effects. These are not included in the table for parsimony.*

Table .53: Violent Crime Models: Tucson

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.00191 | 0.00206 | -0.00229 | 0.00904* | 0.00995*** | 0.00532* | -0.00185 | -0.00299 | -0.00524 |
| % Residential LU | -0.01591*** | -0.01462*** | -0.01308*** | -0.02040*** | -0.01869*** | -0.01681*** | -0.00808 | -0.00687 | -0.00519 |
| % Retail LU | 0.01221*** | 0.01105*** | 0.00893*** | 0.01750*** | 0.01537*** | 0.01321*** | 0.01379 | 0.01440 | 0.01302 |
| % Office LU | 0.01100* | 0.00964** | 0.00411 | 0.02123*** | 0.01810*** | 0.01243*** | 0.00474 | 0.00146 | -0.00245 |
| % School LU | 0.00604* | 0.00287 | -0.00132 | -0.00230 | -0.00213 | -0.00547** | 0.00401 | 0.00934 | 0.00387 |
| # of bars | 0.69426*** | 0.43894*** | 0.46452*** | -0.03672 | -0.21947* | -0.20182 | 1.08207* | 1.01077** | 1.10601** |
| # of grocery stores | 0.38023*** | 0.30100*** | 0.33793*** | 0.80337*** | 0.66781*** | 0.70140*** | -0.15527 | 0.05477 | 0.07939 |
| # of restaurants | 0.18377*** | 0.10243*** | 0.09079*** | 0.36943*** | 0.26855*** | 0.25486*** | -0.08080 | -0.11643 | -0.12461 |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00872*** | -0.00730*** | -0.00846*** | -0.00705*** | -0.00540*** | -0.00651*** | -0.00986* | -0.00943* | -0.01168** |
| % Vacant Units | 0.00439 | 0.00412* | 0.00471* | 0.00779* | 0.00548* | 0.00648** | 0.01100 | 0.01003 | 0.00969 |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.72645*** | 0.72281*** | 0.66079*** | 0.68431*** | 0.67503*** | 0.60009*** | 0.87689*** | 0.81645*** | 0.71972*** |
| % Young People | 0.00232 | 0.00286 | 0.00362* | 0.00288 | 0.00370* | 0.00571*** | -0.01065 | -0.01126 | -0.00979 |
| Ethnic Heterogeneity | -0.00150 | 0.00104 | 0.00363* | 0.00153 | 0.00210 | 0.00432** | 0.00764 | 0.00836 | 0.01141 |
| % Low-income | -0.00157 | -0.00300* | -0.00122 | -0.00617** | -0.00624*** | -0.00365** | 0.01409* | 0.01382* | 0.01062* |

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Table .53 – *Continued from previous page*

| | Assault Yearly | Assault Nightly | Assault Day & Night | Robbery Yearly | Robbery Nightly | Robbery Day & Night | Homicide Yearly | Homicide Nightly | Homicide Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | -0.04721*** | -0.05286*** | -0.05175*** | -0.03987** | -0.04181*** | -0.04014*** | -0.05953 | -0.06579 | -0.07783 |
| % Residential LU | -0.00807 | -0.01064** | -0.00211 | -0.00752 | -0.00344 | 0.00588 | -0.01990 | -0.02039 | -0.01056 |
| % Retail LU | -0.01094 | -0.01167 | -0.00460 | 0.00474 | -0.00421 | 0.00322 | 0.00556 | -0.00157 | 0.00485 |
| % Office LU | -0.31735*** | -0.29704*** | -0.31775*** | -0.23444*** | -0.25107*** | -0.30787*** | -0.12617 | -0.13525 | -0.24344 |
| % School LU | -0.02703 | -0.02574 | -0.01558 | -0.02666 | -0.03992* | -0.02493 | 0.00853 | -0.00681 | 0.00523 |
| # of bars | 0.01617** | 0.02285*** | 0.02114*** | 0.00882 | 0.01606*** | 0.01457*** | 0.01901 | 0.01356 | 0.02110 |
| # of grocery stores | 0.00916 | 0.00450 | 0.00954* | 0.00304 | 0.00173 | 0.00571 | 0.00446 | 0.00472 | 0.00852 |
| # of restaurants | 0.00101 | 0.00158 | 0.00056 | 0.00013 | 0.00064 | 0.00027 | -0.01321 | -0.01097 | -0.01238 |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00118 | -0.00305 | -0.00033 | -0.00353 | -0.00006 | 0.00049 | 0.02106 | 0.01607 | 0.00777 |
| % Vacant Units | -0.04053 | -0.03966* | -0.02336 | -0.09809** | -0.06768** | -0.05221* | 0.03861 | 0.02139 | 0.03459 |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.66169*** | 0.82279*** | 0.44703*** | 1.17609*** | 1.10062*** | 0.61354*** | 2.28065** | 1.99505* | 1.56960** |
| % Young People | -0.04272*** | -0.05092*** | -0.04603*** | -0.02419 | -0.02550** | -0.02666*** | 0.01660 | 0.01224 | -0.00149 |
| Ethnic Heterogeneity | 0.01657** | 0.01209** | 0.00781* | 0.00588 | 0.00340 | 0.00001 | 0.01530 | 0.01385 | 0.00379 |
| % Low-income | 0.05693*** | 0.05659*** | 0.05809*** | 0.05448*** | 0.05428*** | 0.05552*** | 0.01259 | 0.01683 | 0.02240 |
| Intercept | -10.13692*** | -22.23260*** | -18.71844*** | -14.86993*** | -25.26410*** | -20.41578*** | -33.21246*** | -40.92551*** | -35.28113*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. The 'yearly' models also include city fixed effects. These are not included in the table for parsimony.*

Table .54: Property Crime Models: Tucson

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | 0.01937*** | 0.01691*** | 0.01161*** | 0.01298*** | 0.01332*** | 0.00364* | 0.01495*** | 0.01012*** | 0.00145 |
| % Residential LU | -0.01493*** | -0.01617*** | -0.01330*** | -0.01108*** | -0.00941*** | -0.00715*** | -0.00476*** | -0.00529*** | -0.00294*** |
| % Retail LU | 0.03241*** | 0.02924*** | 0.02767*** | 0.01022*** | 0.01270*** | 0.00877*** | 0.00850*** | 0.00751*** | 0.00266** |
| % Office LU | 0.01807*** | 0.01514*** | 0.01006*** | 0.01273*** | 0.01065*** | 0.00064 | 0.00486 | 0.00156 | -0.00905*** |
| % School LU | 0.00521** | 0.00023 | -0.00373*** | 0.00571** | 0.00271* | -0.00289* | 0.00586*** | 0.00233* | -0.00374*** |
| # of bars | 0.52009*** | 0.55842*** | 0.58872*** | 0.37722** | 0.16954** | 0.23226*** | 0.01343 | -0.07020 | -0.00965 |
| # of grocery stores | 1.41863*** | 1.47218*** | 1.52507*** | 0.04674 | -0.01432 | 0.02578 | 0.05969 | -0.01061 | 0.02678 |
| # of restaurants | 0.27564*** | 0.23284*** | 0.21672*** | 0.24196*** | 0.12369*** | 0.11986*** | 0.16520*** | 0.11976*** | 0.12626*** |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.00269*** | -0.00062 | -0.00193*** | -0.01063*** | -0.00946*** | -0.01164*** | -0.00034 | 0.00053 | -0.00302*** |
| % Vacant Units | 0.01300*** | 0.01483*** | 0.01524*** | 0.00362 | 0.00680*** | 0.00775*** | 0.00413** | 0.00652*** | 0.00575*** |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.77710*** | 0.82190*** | 0.72471*** | 0.77821*** | 0.85581*** | 0.73239*** | 0.74522*** | 0.77450*** | 0.63623*** |
| % Young People | 0.00338* | 0.00297*** | 0.00343*** | 0.00246 | 0.00443*** | 0.00494*** | 0.00485*** | 0.00521*** | 0.00299*** |
| Ethnic Heterogeneity | 0.00021 | -0.00064 | 0.00137* | -0.00164 | 0.00007 | 0.00332*** | 0.00140 | 0.00224** | 0.00358*** |
| % Low-income | -0.00320** | -0.00320*** | -0.00188*** | -0.00380** | -0.00315*** | -0.00136* | -0.00332*** | -0.00297*** | -0.00160** |

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Table .54 – *Continued from previous page*

| | Larceny Yearly | Larceny Nightly | Larceny Day & Night | Motor Theft Yearly | Motor Theft Nightly | Motor Theft Day & Night | Burglary Yearly | Burglary Nightly | Burglary Day & Night |
|---|---|---|---|---|---|---|---|---|---|
| **Spatial Lags** | | | | | | | | | |
| **Land Use and Business** | | | | | | | | | |
| % Industrial LU | -0.01125 | -0.01792*** | -0.02255*** | -0.00390 | -0.00596 | -0.00608 | -0.00979 | -0.01230** | -0.00957* |
| % Residential LU | -0.00551* | -0.00478*** | 0.00349** | -0.00575 | -0.00718*** | -0.00059 | 0.00709** | 0.00609*** | 0.01199*** |
| % Retail LU | 0.04021*** | 0.02364*** | 0.02340*** | -0.00156 | -0.01148* | -0.00546 | 0.00706 | 0.00278 | 0.00717* |
| % Office LU | 0.07792* | 0.15088*** | 0.10824*** | -0.03275 | 0.01775 | -0.03565 | 0.15054*** | 0.13435*** | 0.05543** |
| % School LU | -0.01380 | -0.00658 | 0.01111* | -0.03100** | -0.03830*** | -0.01625* | -0.02015* | -0.02111*** | 0.00636 |
| # of bars | 0.00082 | 0.00334 | 0.00487** | 0.01821*** | 0.01605*** | 0.01747*** | -0.00578 | -0.00711** | -0.00281 |
| # of grocery stores | -0.00761* | -0.00516** | -0.00277 | -0.01869*** | -0.01901*** | -0.01533*** | -0.01044*** | -0.01246*** | -0.01070*** |
| # of restaurants | -0.00415*** | -0.00597*** | -0.00601*** | -0.00172 | -0.00109 | -0.00217* | -0.00010 | 0.00020 | -0.00008 |
| **Housing** | | | | | | | | | |
| % Homeowners | -0.01635*** | -0.00898*** | -0.00527* | 0.00091 | 0.00831* | 0.00578 | 0.00761 | 0.01106*** | 0.00690** |
| % Vacant Units | -0.05337*** | -0.05597*** | -0.05856*** | 0.00479 | 0.00449 | 0.01366 | -0.02526* | -0.01816* | -0.01605* |
| **Time Varying** | | | | | | | | | |
| Logged Population | 0.40301*** | 0.73307*** | 0.39043*** | 0.45467*** | 0.55547*** | 0.26614*** | 0.37105*** | 0.41246*** | 0.09827 |
| % Young People | 0.01606** | 0.01753*** | 0.01465*** | -0.00957 | -0.00506 | -0.01200** | 0.02221*** | 0.02424*** | 0.01557*** |
| Ethnic Heterogeneity | -0.00900** | -0.00863*** | -0.01256*** | 0.00860* | 0.00585* | 0.00003 | 0.00671* | 0.00866*** | 0.00600** |
| % Low-income | 0.00185 | 0.00881** | 0.01711*** | 0.03732*** | 0.03851*** | 0.03872*** | 0.03012*** | 0.03287*** | 0.03348*** |
| Intercept | -3.47346** | -17.73432*** | -14.14451*** | -7.40527*** | -19.33511*** | -15.47368*** | -8.55865*** | -19.49206*** | -15.01289*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: The 'nightly' and 'day and night' models include city and time interval fixed effects. The 'yearly' models also include city fixed effects. These are not included in the table for parsimony.*

# Appendix F: Models for each Time of Day for Los Angeles

See next page.

Table .55: Los Angeles: Winter Assault

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.01571*** | 0.00606 | 0.00248 | 0.00609 | 0.01013 | -0.00245 | -0.00132 |
| % Residential LU | -0.00885*** | -0.00306 | -0.00273 | -0.00727* | -0.00088 | -0.00864** | -0.00719 |
| % Retail LU | 0.00344 | 0.01132* | 0.00872** | 0.00562 | 0.01673*** | 0.00724* | 0.01124* |
| % Office LU | -0.01136* | -0.00223 | -0.00046 | -0.00480 | 0.00708 | -0.01205* | -0.00473 |
| % School LU | -0.00740 | 0.01241* | 0.00312 | 0.00096 | -0.00168 | -0.00574 | -0.01707 |
| # of bars | -0.68496 | -0.26445 | 0.08808 | 0.71775** | 0.37528 | 0.65601** | 0.45070 |
| # of grocery stores | 0.40852*** | -0.09356 | 0.18846* | -0.03562 | 0.19432 | 0.17438 | 0.23106 |
| # of restaurants | -0.01805 | -0.06129 | 0.15588*** | 0.22206*** | 0.14053* | 0.08234 | 0.14508* |
| **Housing** | | | | | | | |
| % Homeowners | -0.00674*** | -0.00418 | -0.01103*** | -0.00665** | -0.00995*** | -0.00962*** | -0.00710* |
| % Vacant Units | 0.01072 | 0.00217 | 0.01693*** | 0.01396* | 0.02176** | 0.01408* | 0.02330* |
| **Time Varying** | | | | | | | |
| Logged Population | 0.69306*** | 0.66930*** | 0.60701*** | 0.57649*** | 0.64005*** | 0.56733*** | 0.62106*** |
| % Young People | 0.00538 | 0.00070 | -0.00299 | 0.00094 | -0.02079* | 0.00417 | 0.00522 |
| Ethnic Heterogeneity | 0.00479 | 0.00246 | 0.00299 | -0.00516 | 0.00434 | -0.00374 | -0.00131 |
| % Low-income | 0.00022 | 0.00439 | 0.00083 | 0.00039 | -0.00251 | 0.00046 | 0.00167 |

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Table .55 – *Continued from previous page*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.04975*** | 0.00824 | 0.02149** | 0.01226 | 0.02267 | 0.02057* | 0.00266 |
| % Residential LU | 0.01822** | -0.00410 | -0.00970 | -0.00305 | -0.00528 | 0.00230 | 0.00531 |
| % Retail LU | 0.04824 | 0.03131 | -0.00732 | 0.01376 | 0.01728 | 0.02679 | -0.08313 |
| % Office LU | -0.06351 | -0.09140* | -0.07261* | -0.01616 | -0.06851 | 0.04762 | -0.02821 |
| % School LU | 0.04454 | 0.03481 | -0.04672 | -0.03581 | -0.19296*** | 0.00950 | -0.20400*** |
| # of bars | 0.00902 | 0.01322 | 0.00612 | 0.01900*** | -0.00332 | 0.01488** | 0.02492*** |
| # of grocery stores | 0.00009 | -0.00390 | -0.00352* | -0.00066 | -0.00555* | -0.00131 | 0.00496 |
| # of restaurants | -0.00193** | -0.00100 | -0.00154** | -0.00205** | -0.00150 | -0.00281*** | -0.00235* |
| **Housing** | | | | | | | |
| % Homeowners | 0.02202* | 0.00680 | 0.04350*** | 0.03677*** | 0.04954*** | 0.03373*** | 0.05365*** |
| % Vacant Units | 0.30688*** | 0.10204 | 0.23082*** | 0.09396 | 0.24048*** | 0.14039** | 0.11058 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.56879 | 0.52636 | 1.78063*** | 1.45703** | 1.74782** | 1.22939** | 1.57179** |
| % Young People | -0.14352*** | -0.07383 | -0.05368* | 0.00578 | 0.03184 | -0.06034* | 0.03229 |
| Ethnic Heterogeneity | 0.00861 | -0.01585 | 0.00406 | 0.01142 | 0.00078 | -0.00829 | 0.01464 |
| % Low-income | 0.06334*** | 0.04172** | 0.05514*** | 0.03774** | 0.06617*** | 0.04886*** | 0.03012 |
| Intercept | -24.03370*** | -18.86685*** | -36.62409*** | -34.03637*** | -38.82183*** | -28.50340*** | -35.89893*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: LU = Land Use. Table is unstandardized coefficients.*

Table .56: Los Angeles: Spring Assault

| | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00744 | -0.00108 | -0.00196 | 0.00167 | -0.00158 | 0.00051 | -0.00171 |
| % Residential LU | -0.00875*** | -0.00011 | -0.00738*** | -0.00873*** | -0.00455 | -0.00476 | -0.00722* |
| % Retail LU | -0.00108 | 0.00885 | 0.00571* | 0.00642 | 0.00898* | 0.01153*** | 0.00910* |
| % Office LU | -0.00492 | -0.00042 | -0.00310 | -0.00497 | 0.00245 | -0.00449 | -0.00689 |
| % School LU | -0.00490 | 0.01078 | 0.00235 | -0.00983 | -0.00441 | -0.00439 | 0.00067 |
| # of bars | -0.17165 | -0.14846 | 0.46904* | 0.34602 | 0.21076 | 0.46970 | 1.10873*** |
| # of grocery stores | 0.09165 | 0.02371 | 0.16855 | 0.25449* | 0.09639 | 0.31086** | 0.15578 |
| # of restaurants | 0.06932 | 0.02483 | -0.03227 | 0.09723* | 0.10285 | 0.06652 | 0.20227** |
| **Housing** | | | | | | | |
| % Homeowners | -0.01005*** | -0.00515 | -0.00994*** | -0.01159*** | -0.00982*** | -0.00838*** | -0.00959*** |
| % Vacant Units | 0.00868 | 0.01114 | 0.01295** | 0.01257* | 0.00486 | 0.01011 | 0.00441 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.54721*** | 0.67482*** | 0.58071*** | 0.53621*** | 0.58962*** | 0.59178*** | 0.47835*** |
| % Young People | -0.00684 | 0.01080 | -0.00530 | -0.00210 | -0.00064 | 0.00770 | -0.00264 |
| Ethnic Heterogeneity | 0.00459 | 0.00228 | -0.00124 | 0.00296 | -0.00374 | -0.00151 | 0.00112 |
| % Low-income | 0.00123 | -0.00266 | -0.00019 | 0.00612* | -0.00372 | 0.00170 | -0.00134 |

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Table .56 – *Continued from previous page*

| | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.02702** | 0.03993** | 0.02096** | 0.02696** | 0.03538*** | 0.01496 | 0.00825 |
| % Residential LU | 0.00310 | 0.00873 | 0.00280 | 0.01963* | 0.00648 | -0.01345 | 0.00167 |
| % Retail LU | -0.02832 | 0.02518 | 0.03952 | 0.02847 | 0.01440 | -0.00614 | 0.04887 |
| % Office LU | 0.00373 | -0.04596 | -0.05756* | -0.04962 | -0.05552 | 0.01813 | 0.01543 |
| % School LU | -0.05533 | 0.01763 | 0.00397 | -0.01756 | 0.00538 | -0.01411 | -0.06621 |
| # of bars | 0.00502 | -0.00127 | -0.00207 | 0.01896*** | -0.00065 | 0.01372** | 0.01984** |
| # of grocery stores | 0.00460* | -0.00009 | -0.00390* | -0.00263 | -0.00332 | 0.00050 | -0.00145 |
| # of restaurants | -0.00248*** | -0.00044 | -0.00048 | -0.00128* | -0.00050 | -0.00307*** | -0.00225** |
| **Housing** | | | | | | | |
| % Homeowners | 0.03495*** | 0.02756* | 0.03294*** | 0.02335** | 0.04576*** | 0.02315** | 0.04060*** |
| % Vacant Units | 0.27107*** | 0.26171*** | 0.17902*** | 0.17273*** | 0.28042*** | 0.08359 | 0.17095** |
| **Time Varying** | | | | | | | |
| Logged Population | 0.81319** | 0.47608 | 1.00531*** | 0.15680 | 0.82587 | 1.52211*** | 0.92340* |
| % Young People | -0.04685 | -0.09719* | -0.08956*** | -0.07590** | -0.08285* | -0.12132*** | -0.05094 |
| Ethnic Heterogeneity | 0.01431* | -0.01196 | -0.00076 | 0.00342 | 0.00563 | 0.00873 | -0.00463 |
| % Low-income | 0.07775*** | 0.04655*** | 0.06575*** | 0.06548*** | 0.07999*** | 0.04576*** | 0.06357*** |
| Intercept | -27.16148*** | -21.42129*** | -26.19040*** | -18.15160*** | -27.09290*** | -29.79058*** | -25.69506*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: LU = Land Use. Table is unstandardized coefficients.*

Table .57: Los Angeles: Summer Assault

| | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|
| | 7am-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | |
| % Industrial LU | -0.00121 | -0.00864* | -0.00546 | 0.00972 | -0.00285 | -0.00216 |
| % Residential LU | -0.00187 | -0.00969*** | -0.00875*** | -0.00431 | -0.00595* | -0.00619 |
| % Retail LU | 0.00433 | 0.00358 | 0.01101*** | 0.00573 | 0.00718* | 0.01208** |
| % Office LU | -0.00258 | -0.00871* | -0.00055 | -0.00126 | -0.00386 | -0.00008 |
| % School LU | -0.00511 | -0.00354 | -0.00688 | 0.00520 | 0.00038 | -0.00992 |
| # of bars | 0.02573 | -0.25891 | 0.40985 | 0.32601 | 0.49380* | 0.51607 |
| # of grocery stores | 0.15654 | 0.30177*** | 0.24001* | 0.37058** | 0.07876 | 0.25185 |
| # of restaurants | 0.05963 | 0.08450* | 0.06796 | 0.00763 | 0.17647*** | 0.16905** |
| **Housing** | | | | | | |
| % Homeowners | -0.01325*** | -0.01036*** | -0.01193*** | -0.01460*** | -0.00929*** | -0.00854** |
| % Vacant Units | 0.00673 | 0.01008* | 0.00871 | 0.00667 | 0.00764 | 0.00049 |
| **Time Varying** | | | | | | |
| Logged Population | 0.52895*** | 0.60552*** | 0.55935*** | 0.44605*** | 0.53814*** | 0.54440*** |
| % Young People | 0.00613 | 0.00385 | 0.00434 | 0.00456 | -0.00444 | 0.00245 |
| Ethnic Heterogeneity | 0.00204 | -0.00346 | 0.00076 | 0.00373 | -0.00523* | 0.00222 |
| % Low-income | 0.00044 | -0.00094 | 0.00271 | 0.00397 | 0.00302 | 0.00243 |

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Table .57 – *Continued from previous page*

| | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|
| | 7am-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | |
| **Land Use and Business** | | | | | | |
| % Industrial LU | 0.01953* | 0.02135** | 0.03523*** | 0.02457* | 0.02748*** | 0.03298** |
| % Residential LU | 0.00008 | 0.00502 | 0.02425** | 0.01808 | -0.00483 | 0.00146 |
| % Retail LU | -0.00947 | -0.01195 | -0.02379 | -0.02349 | 0.00880 | 0.07500 |
| % Office LU | -0.02524 | -0.03491 | 0.02757 | 0.00803 | -0.03454 | -0.05161 |
| % School LU | -0.06640* | -0.01755 | -0.08768** | -0.05762 | -0.03470 | -0.08192 |
| # of bars | 0.00776 | 0.00412 | 0.01818*** | 0.00879 | 0.00254 | 0.01780** |
| # of grocery stores | 0.00386* | -0.00226 | -0.00114 | 0.00161 | -0.00232 | 0.00027 |
| # of restaurants | -0.00252*** | -0.00159** | -0.00172** | -0.00141 | -0.00142* | -0.00218** |
| **Housing** | | | | | | |
| % Homeowners | 0.04507*** | 0.02764*** | 0.05350*** | 0.05553*** | 0.03110*** | 0.03756*** |
| % Vacant Units | 0.29095*** | 0.16818*** | 0.29130*** | 0.21854*** | 0.14519*** | 0.15264** |
| **Time Varying** | | | | | | |
| Logged Population | 1.07771*** | 0.84004** | 0.93287* | 0.82107 | 1.32282*** | 1.37355** |
| % Young People | -0.10488*** | -0.06841*** | -0.03970 | -0.03702 | -0.03429 | -0.03897 |
| Ethnic Heterogeneity | 0.00814 | 0.00651 | 0.00705 | 0.01430 | 0.00568 | 0.00329 |
| % Low-income | 0.06724*** | 0.06670*** | 0.06239*** | 0.06376*** | 0.03569** | 0.03443* |
| Intercept | -28.97913*** | -24.28601*** | -30.24961*** | -28.41117*** | -29.21219*** | -31.62013*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .58: Los Angeles: Fall Assault

| | 21 | 22 | 23 | 24 | 25 | 26 | 27 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00541 | -0.00881 | -0.00199 | 0.00335 | 0.00596 | 0.00632 | 0.00539 |
| % Residential LU | -0.00418 | -0.00253 | -0.01162*** | -0.00777** | -0.00754* | -0.00133 | -0.00953** |
| % Retail LU | 0.00395 | 0.01125* | 0.00080 | 0.00783* | 0.00710 | 0.01513*** | 0.00697 |
| % Office LU | -0.00720 | -0.00217 | -0.01046** | -0.00474 | -0.00267 | 0.00159 | -0.01409* |
| % School LU | -0.00398 | 0.01413* | -0.01142* | -0.01170 | -0.00027 | -0.00364 | -0.00239 |
| # of bars | -0.64673 | 0.47928 | 0.62502** | 0.50229* | -0.45823 | 0.29533 | 0.59599 |
| # of grocery stores | 0.27679* | 0.20308 | 0.07120 | 0.08290 | 0.24798 | 0.16283 | 0.28018 |
| # of restaurants | 0.00167 | -0.04936 | 0.07858 | 0.20487*** | 0.08330 | 0.10980* | 0.16388** |
| **Housing** | | | | | | | |
| % Homeowners | -0.00957*** | -0.01369*** | -0.00878*** | -0.00946*** | -0.00844** | -0.01156*** | -0.00911*** |
| % Vacant Units | 0.00152 | 0.00287 | 0.01466** | 0.01795** | 0.00965 | 0.01273* | 0.01706* |
| **Time Varying** | | | | | | | |
| Logged Population | 0.61073*** | 0.59596*** | 0.62440*** | 0.51761*** | 0.73292*** | 0.58689*** | 0.48054*** |
| % Young People | 0.00728 | 0.00806 | 0.00233 | 0.00306 | -0.00720 | 0.00205 | -0.00469 |
| Ethnic Heterogeneity | 0.00626* | -0.00753 | 0.00012 | 0.00080 | -0.00427 | -0.00680* | -0.00046 |
| % Low-income | 0.00004 | 0.00540 | 0.00165 | -0.00552 | 0.00179 | -0.00184 | 0.00181 |

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Table .58 – *Continued from previous page*

| | 21 | 22 | 23 | 24 | 25 | 26 | 27 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.04857*** | 0.03292* | 0.02248** | 0.01873 | 0.01781 | 0.02446** | 0.01033 |
| % Residential LU | 0.01822** | 0.00013 | 0.00306 | 0.00722 | 0.00067 | 0.00351 | 0.00083 |
| % Retail LU | -0.05093 | 0.03081 | 0.00743 | 0.10210** | 0.04657 | -0.01080 | -0.02470 |
| % Office LU | 0.01829 | -0.06020 | -0.06417* | -0.02066 | -0.17970*** | -0.02032 | 0.04899 |
| % School LU | -0.02380 | -0.09136 | -0.01786 | -0.03688 | -0.00760 | -0.03824 | 0.02260 |
| # of bars | 0.01285* | 0.00640 | 0.00682 | 0.01407** | 0.01913** | 0.00997* | 0.02377*** |
| # of grocery stores | 0.00642*** | -0.00086 | -0.00532** | -0.00427 | -0.00148 | -0.00089 | -0.00052 |
| # of restaurants | -0.00255*** | -0.00236* | -0.00082 | -0.00181** | -0.00076 | -0.00196** | -0.00130 |
| **Housing** | | | | | | | |
| % Homeowners | 0.03717*** | 0.05116*** | 0.03964*** | 0.03551*** | 0.05577*** | 0.03601*** | 0.03730*** |
| % Vacant Units | 0.32809*** | 0.18892** | 0.15961*** | 0.21393*** | 0.32366*** | 0.14312** | -0.03805 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.55938* | 1.31989** | 1.21392*** | 0.71036 | 0.91926* | 0.76429* | 0.70269 |
| % Young People | -0.10735*** | -0.07259 | -0.04605* | -0.01389 | -0.06306 | -0.01278 | -0.01482 |
| Ethnic Heterogeneity | 0.00950 | 0.02638* | 0.00015 | 0.00543 | 0.00989 | 0.01162* | -0.00137 |
| % Low-income | 0.07216*** | 0.04197** | 0.07154*** | 0.06268*** | 0.05177** | 0.06958*** | 0.05973*** |
| Intercept | -25.23069*** | -32.01109*** | -29.99284*** | -26.39408*** | -28.99513*** | -25.60404*** | -22.77989*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .59: Los Angeles: Winter Robbery

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00369 | 0.00233 | -0.00161 | -0.00011 | -0.00424 | -0.00112 | 0.00079 |
| % Residential LU | -0.00572** | -0.00797** | -0.00973*** | -0.00851*** | -0.01525*** | -0.00797*** | -0.01219*** |
| % Retail LU | 0.01202*** | 0.01722*** | 0.01207*** | 0.01515*** | 0.01070*** | 0.01464*** | 0.00720* |
| % Office LU | -0.00260 | -0.00617 | -0.00201 | 0.00026 | -0.00499 | 0.00116 | -0.00830 |
| % School LU | -0.00163 | 0.01188** | 0.00421 | -0.00051 | -0.00061 | -0.00183 | -0.01567* |
| # of bars | 0.28077 | -0.23641 | 0.20805 | 0.40171* | -0.86470* | -0.03805 | 0.32705 |
| # of grocery stores | 0.22652** | 0.31421** | 0.37844*** | 0.20298* | 0.28995** | 0.30020*** | 0.49138*** |
| # of restaurants | 0.09735** | 0.01332 | 0.15628*** | 0.12854*** | 0.18881*** | 0.13594*** | 0.08404 |
| **Housing** | | | | | | | |
| % Homeowners | -0.00560*** | 0.00110 | -0.00861*** | -0.00675*** | -0.00909*** | -0.00742*** | -0.00721* |
| % Vacant Units | 0.00128 | 0.00386 | 0.00469 | 0.00334 | 0.00435 | 0.00933 | 0.00731 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.48501*** | 0.58474*** | 0.44641*** | 0.51006*** | 0.38895*** | 0.48505*** | 0.35712*** |
| % Young People | 0.00313 | 0.00504 | -0.00389 | 0.00413 | -0.00628 | -0.00482 | 0.00827 |
| Ethnic Heterogeneity | 0.00431 | 0.00169 | 0.00195 | 0.00298 | 0.00247 | 0.00288 | -0.00002 |
| % Low-income | 0.00139 | 0.00426 | 0.00097 | -0.00146 | -0.00353 | -0.00270 | -0.00524 |

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Table .59 – *Continued from previous page*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.04081*** | 0.02514* | 0.02715*** | 0.00164 | 0.05141*** | 0.02497** | -0.02003 |
| % Residential LU | 0.02274*** | 0.01339 | 0.02411*** | 0.00238 | 0.03907*** | 0.02082** | 0.02303 |
| % Retail LU | 0.02710 | -0.01645 | 0.00055 | 0.08860** | -0.00595 | 0.06790* | 0.04022 |
| % Office LU | -0.01215 | -0.10583** | 0.04430* | -0.02848 | -0.04267 | 0.01454 | 0.05121 |
| % School LU | 0.01880 | 0.03350 | -0.03004 | -0.11162*** | 0.01851 | 0.00040 | -0.07341 |
| # of bars | -0.00434 | 0.00099 | 0.00315 | 0.00275 | 0.00858 | 0.00750* | 0.01299* |
| # of grocery stores | -0.00054 | -0.00286 | -0.00215 | -0.00180 | -0.00153 | -0.00253 | -0.00051 |
| # of restaurants | -0.00107* | 0.00010 | -0.00098* | -0.00093 | -0.00067 | -0.00086 | -0.00042 |
| **Housing** | | | | | | | |
| % Homeowners | 0.01188 | 0.00970 | 0.01397* | 0.01324 | 0.00607 | 0.00074 | 0.01498 |
| % Vacant Units | 0.13708*** | 0.10730* | 0.04953 | 0.09243* | 0.09380 | -0.06619 | -0.04514 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.85611*** | 0.70866* | 0.74886** | 1.17103** | 0.31753 | 0.53371 | 0.03778 |
| % Young People | -0.02047 | -0.06743* | 0.00572 | 0.02611 | -0.03968 | 0.00091 | -0.00889 |
| Ethnic Heterogeneity | -0.00843 | 0.00533 | -0.00116 | 0.00304 | 0.00017 | -0.00952 | -0.00138 |
| % Low-income | 0.04577*** | 0.04416*** | 0.03969*** | 0.01385 | 0.06173*** | 0.03136** | 0.07421*** |
| Intercept | -26.17039*** | -22.75521*** | -23.46671*** | -29.17554*** | -19.12953*** | -19.64280*** | -15.33050** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .60: Los Angeles: Spring Robbery

| | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00676* | -0.00293 | -0.00632* | 0.00177 | 0.00190 | -0.00950* | -0.00100 |
| % Residential LU | -0.00832*** | -0.00976*** | -0.01242*** | -0.01036*** | -0.00976*** | -0.01194*** | -0.01103*** |
| % Retail LU | 0.01076*** | 0.00721* | 0.01008*** | 0.01138*** | 0.01421*** | 0.00874*** | 0.00817* |
| % Office LU | -0.00771* | -0.00300 | -0.00280 | -0.00228 | 0.00058 | -0.00269 | 0.00010 |
| % School LU | -0.00033 | 0.00933** | -0.00843* | -0.00210 | 0.00127 | -0.00130 | -0.00283 |
| # of bars | 0.01714 | -0.49508 | 0.02590 | 0.33612 | 0.18650 | 0.10233 | 0.40084 |
| # of grocery stores | 0.26182*** | 0.33786*** | 0.33714*** | 0.22539* | 0.13020 | 0.47751*** | 0.38668*** |
| # of restaurants | 0.13873*** | 0.09871** | 0.12904*** | 0.11803** | 0.15739*** | 0.09304** | 0.16164*** |
| **Housing** | | | | | | | |
| % Homeowners | -0.00711*** | -0.00431* | -0.00733*** | -0.00795*** | -0.00691** | -0.01041*** | -0.00452 |
| % Vacant Units | 0.00386 | 0.00248 | 0.00247 | 0.00940* | 0.01432** | 0.01200** | 0.00549 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.44595*** | 0.52088*** | 0.39660*** | 0.48891*** | 0.38185*** | 0.43889*** | 0.56195*** |
| % Young People | 0.00647* | 0.00247 | -0.00087 | -0.00182 | -0.00152 | -0.00869 | 0.00426 |
| Ethnic Heterogeneity | 0.00552* | -0.00233 | 0.00187 | 0.00840*** | -0.00432 | -0.00042 | -0.00246 |
| % Low-income | -0.00256 | 0.00581** | -0.00300 | -0.00092 | -0.00376 | 0.00128 | 0.00438 |

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Table .60 – *Continued from previous page*

| | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.04135*** | 0.02873** | 0.03579*** | 0.01491 | 0.04052*** | 0.00687 | -0.00482 |
| % Residential LU | 0.02635*** | 0.02241** | 0.01450* | 0.00859 | 0.02649* | 0.02745*** | 0.01782 |
| % Retail LU | 0.02371 | -0.05858 | 0.05590* | 0.03256 | 0.06994 | 0.02264 | 0.04435 |
| % Office LU | 0.00651 | -0.02451 | -0.01916 | -0.00256 | 0.02070 | 0.03702 | -0.02746 |
| % School LU | -0.05805* | -0.01274 | -0.04823* | -0.03829 | 0.01445 | -0.07615* | -0.07939 |
| # of bars | -0.00266 | -0.00011 | -0.00099 | 0.01600*** | 0.00220 | 0.00749 | 0.00695 |
| # of grocery stores | 0.00308* | -0.00087 | -0.00298* | -0.00181 | -0.00204 | 0.00214 | -0.00163 |
| # of restaurants | -0.00156** | -0.00059 | -0.00081* | -0.00184*** | -0.00146* | -0.00093 | -0.00002 |
| **Housing** | | | | | | | |
| % Homeowners | 0.02576*** | 0.01535 | 0.01857** | 0.01650* | 0.02643** | 0.01456* | 0.01725 |
| % Vacant Units | 0.18052*** | 0.04086 | 0.15179*** | 0.12017** | 0.11781* | 0.02028 | 0.10882 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.88324*** | 0.98605*** | 1.28006*** | 1.34140*** | 1.12803* | 0.33029 | 0.56631 |
| % Young People | -0.04903* | -0.05959* | -0.03543* | -0.01297 | -0.04219 | 0.01065 | 0.01007 |
| Ethnic Heterogeneity | 0.00022 | 0.00648 | -0.00098 | -0.00681 | 0.00521 | -0.00858 | -0.00786 |
| % Low-income | 0.06334*** | 0.04149*** | 0.03131*** | 0.03265** | 0.06134*** | 0.03094** | 0.03384* |
| Intercept | -27.30537*** | -25.13795*** | -28.63234*** | -30.68077*** | -30.05631*** | -17.69967*** | -22.35559*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: LU = Land Use. Table is unstandardized coefficients.*

Table .61: Los Angeles: Summer Robbery

| | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|
| | 7am-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | |
| % Industrial LU | -0.00639* | 0.00026 | -0.00435 | 0.00026 | -0.00166 | 0.00474 |
| % Residential LU | -0.00751*** | -0.01117*** | -0.01131*** | -0.01404*** | -0.01161*** | -0.01074*** |
| % Retail LU | 0.01256*** | 0.01278*** | 0.01160*** | 0.01167*** | 0.00901*** | 0.01422*** |
| % Office LU | -0.00374 | -0.00168 | -0.00135 | 0.00145 | -0.01376*** | -0.00414 |
| % School LU | -0.00468 | 0.00611* | -0.00317 | -0.00441 | -0.00691 | -0.00371 |
| # of bars | 0.02249 | 0.01486 | 0.21225 | -0.14070 | 0.17554 | -0.00094 |
| # of grocery stores | 0.34235*** | 0.39209*** | 0.38263*** | 0.19125 | 0.22006* | 0.27580* |
| # of restaurants | 0.06858* | 0.18780*** | 0.10075** | 0.14120*** | 0.18422*** | 0.04890 |
| **Housing** | | | | | | |
| % Homeowners | -0.00249* | -0.00537*** | -0.00876*** | -0.00197 | -0.00448* | -0.00515* |
| % Vacant Units | 0.00500 | 0.00951* | 0.00958* | 0.00324 | 0.01289** | 0.01987*** |
| **Time Varying** | | | | | | |
| Logged Population | 0.49100*** | 0.47814*** | 0.45594*** | 0.41426*** | 0.50346*** | 0.43820*** |
| % Young People | 0.00929*** | -0.00775* | -0.00471 | -0.00299 | -0.00595 | 0.00018 |
| Ethnic Heterogeneity | 0.00406* | 0.00177 | 0.00473* | 0.00242 | 0.00095 | -0.00082 |
| % Low-income | -0.00082 | 0.00111 | -0.00083 | 0.00397 | -0.00097 | -0.00349 |

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Table .61 – *Continued from previous page*

| | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|
| | 7am-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | |
| **Land Use and Business** | | | | | | |
| % Industrial LU | 0.03951*** | 0.02098** | 0.02557** | 0.02721* | 0.02271* | 0.00450 |
| % Residential LU | 0.02174*** | 0.01076 | 0.01542* | 0.02846** | 0.02122* | 0.00916 |
| % Retail LU | 0.00406 | 0.03796 | 0.04981 | -0.03231 | 0.05843* | 0.06535 |
| % Office LU | -0.01034 | -0.02802 | -0.02590 | 0.04071 | 0.03055 | -0.02149 |
| % School LU | 0.01317 | 0.01671 | -0.00821 | -0.02134 | -0.05320 | -0.02764 |
| # of bars | -0.00612 | 0.00760* | 0.01258*** | 0.01460** | 0.01294*** | 0.01753*** |
| # of grocery stores | 0.00062 | -0.00199 | -0.00282 | 0.00078 | -0.00221 | -0.00158 |
| # of restaurants | -0.00037 | -0.00154*** | -0.00076 | -0.00110 | -0.00108* | -0.00114 |
| **Housing** | | | | | | |
| % Homeowners | 0.01785** | 0.01780** | 0.00504 | 0.02614** | 0.03284*** | 0.03021** |
| % Vacant Units | 0.20331*** | 0.13105*** | 0.11616** | 0.03076 | 0.05911 | 0.06803 |
| **Time Varying** | | | | | | |
| Logged Population | 0.58676** | 1.15436*** | 0.41156 | 0.68552 | 1.07630** | 1.41984** |
| % Young People | -0.05227** | -0.03271 | -0.01607 | -0.02747 | 0.02880 | -0.00225 |
| Ethnic Heterogeneity | -0.00028 | 0.00143 | -0.00175 | -0.00382 | 0.00034 | -0.00023 |
| % Low-income | 0.06607*** | 0.03874*** | 0.03625*** | 0.06253*** | 0.04443*** | 0.02930* |
| Intercept | -23.86712*** | -27.91830*** | -19.46072*** | -24.05440*** | -29.37832*** | -31.53650*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .62: Los Angeles: Fall Robbery

| | 21 | 22 | 23 | 24 | 25 | 26 | 27 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00491 | 0.00186 | -0.00526 | 0.00015 | -0.00030 | -0.00242 | 0.00250 |
| % Residential LU | -0.00646** | -0.00723* | -0.01263*** | -0.00838*** | -0.01242*** | -0.01159*** | -0.00613 |
| % Retail LU | 0.01241*** | 0.01620*** | 0.00904*** | 0.00949*** | 0.01876*** | 0.00953*** | 0.01556*** |
| % Office LU | -0.00264 | -0.00284 | 0.00110 | -0.00072 | -0.00248 | -0.00463 | 0.00799 |
| % School LU | -0.00062 | 0.01131** | -0.00129 | -0.00379 | 0.00712 | -0.00133 | 0.00773 |
| # of bars | -0.07224 | -0.65715 | 0.23720 | 0.06653 | 0.10205 | 0.44813** | 0.44562* |
| # of grocery stores | 0.25710** | 0.23536* | 0.35275*** | 0.31637*** | 0.49863*** | 0.23122** | 0.05034 |
| # of restaurants | 0.16165*** | 0.05854 | 0.16373*** | 0.19416*** | 0.05278 | 0.18103*** | 0.18106*** |
| **Housing** | | | | | | | |
| % Homeowners | -0.00605*** | -0.00201 | -0.00600*** | -0.01192*** | -0.00593* | -0.00671*** | -0.00851** |
| % Vacant Units | 0.00894* | 0.01331* | 0.00611 | 0.00607 | 0.00601 | 0.00383 | 0.00981 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.48816*** | 0.52914*** | 0.41800*** | 0.38329*** | 0.47322*** | 0.38764*** | 0.43946*** |
| % Young People | 0.00703* | 0.00479 | 0.00315 | -0.00088 | -0.00364 | -0.00369 | -0.00263 |
| Ethnic Heterogeneity | 0.00176 | 0.00290 | 0.00116 | 0.00197 | 0.00007 | -0.00085 | 0.00115 |
| % Low-income | -0.00187 | 0.00227 | 0.00092 | -0.00302 | -0.00051 | -0.00011 | 0.00101 |

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Table .62 – *Continued from previous page*

| | 21 | 22 | 23 | 24 | 25 | 26 | 27 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.04076*** | 0.03457** | 0.01791** | 0.01342 | 0.03015** | 0.02375** | 0.01246 |
| % Residential LU | 0.01537** | 0.02054** | 0.00841 | 0.02382** | 0.01074 | 0.01835* | 0.02681* |
| % Retail LU | -0.06149* | -0.06870 | 0.03124 | 0.03831 | -0.05556 | 0.05167 | -0.02398 |
| % Office LU | -0.00007 | -0.01783 | -0.04749* | 0.01966 | -0.00986 | -0.00150 | 0.07850* |
| % School LU | 0.02660 | 0.09362* | 0.00079 | -0.05695 | 0.03428 | 0.01228 | -0.00003 |
| # of bars | 0.00859* | 0.01433* | 0.00541 | 0.01673*** | -0.00806 | 0.00826* | 0.01895*** |
| # of grocery stores | 0.00235 | -0.00233 | -0.00398** | 0.00127 | -0.00240 | -0.00270 | 0.00214 |
| # of restaurants | -0.00231*** | -0.00030 | -0.00061 | -0.00134** | 0.00047 | -0.00058 | -0.00101 |
| **Housing** | | | | | | | |
| % Homeowners | 0.02129** | 0.01793 | 0.01352* | 0.02052** | 0.04359*** | 0.01816* | 0.02936** |
| % Vacant Units | 0.23229*** | 0.00581 | 0.13067*** | 0.08096* | 0.15059** | 0.02762 | -0.00151 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.98090*** | 1.01293** | 1.09261*** | 0.45385 | 1.49885** | 0.64013* | 0.34942 |
| % Young People | -0.03393 | -0.10030** | -0.05917*** | 0.01853 | -0.09663** | -0.02357 | 0.01766 |
| Ethnic Heterogeneity | 0.01172* | -0.00794 | -0.00166 | 0.00050 | 0.01029 | -0.00232 | 0.00083 |
| % Low-income | 0.07885*** | 0.06377*** | 0.03118*** | 0.03875*** | 0.06666*** | 0.04869*** | 0.06055*** |
| Intercept | -29.44971*** | -25.72872*** | -25.25255*** | -21.61786*** | -33.46674*** | -21.34916*** | -21.62080*** |

$*p < .05; **p < .01; ***p < .001$

*Note:*

Table .63: Los Angeles: Winter Homicide

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00342 | | 0.00236 | -0.00426 | -0.00122 | 0.01854 | -0.00356 |
| % Residential LU | -0.00687 | 0.09836 | -0.01938** | -0.01613 | -0.01663 | 0.00699 | -0.01663 |
| % Retail LU | -0.00299 | 0.03378 | -0.00477 | 0.02306 | 0.03052 | -0.01745 | -0.01070 |
| % Office LU | -0.02934 | 0.09466 | -0.01816 | -0.04296 | -0.03260 | -0.04836 | -0.00918 |
| % School LU | 0.00887 | | -0.01118 | | | -0.03459 | -0.06118 |
| # of bars | 0.98792 | | | | | | 0.89209 |
| # of grocery stores | 0.32592 | 0.78001 | -0.21536 | 0.13723 | -0.45001 | 0.11015 | 0.01700 |
| # of restaurants | 0.27664* | -0.62441 | 0.21695 | -0.13114 | 0.24811 | 0.49234** | -0.06616 |
| **Housing** | | | | | | | |
| % Homeowners | 0.00074 | 0.01129 | -0.01399 | 0.02571** | -0.00911 | -0.03263** | -0.01129 |
| % Vacant Units | -0.00059 | 0.02151 | -0.00181 | 0.04233* | 0.02285 | -0.00831 | -0.01738 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.43068* | 1.77290* | 0.57255** | 1.26847*** | 2.32009*** | 0.48939 | 0.27364 |
| % Young People | -0.00233 | 0.02298 | 0.01626 | 0.04659 | -0.07132 | -0.00202 | -0.01873 |
| Ethnic Heterogeneity | 0.00568 | -0.06271 | -0.01279 | -0.02894* | 0.00317 | 0.01478 | 0.01340 |
| % Low-income | 0.00064 | 0.04746* | -0.00055 | 0.01759 | 0.00550 | -0.00787 | 0.02748 |

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Table .63 – *Continued from previous page*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.03849 | -0.29952 | 0.00689 | 0.11024* | 0.05844 | 0.08722 | -0.06865 |
| % Residential LU | -0.00969 | 0.00552 | 0.00721 | 0.03760 | 0.05346 | 0.03294 | -0.06879 |
| % Retail LU | -0.11410 | 0.67777 | -0.29984* | -0.34513 | 0.09596 | -0.24737 | 0.07155 |
| % Office LU | 0.12690 | -0.22664 | 0.11833 | -0.33419 | 0.08895 | 0.10632 | -0.19541 |
| % School LU | 0.19063 | -2.68949* | -0.11086 | -0.15352 | -0.57805 | 0.31797 | 0.16604 |
| # of bars | -0.00676 | 0.01447 | 0.00212 | 0.00805 | 0.04955 | 0.00100 | 0.00047 |
| # of grocery stores | 0.00171 | 0.01509 | -0.00206 | 0.00397 | 0.03038* | 0.01118 | -0.02350 |
| # of restaurants | -0.00261 | -0.00748 | -0.00620 | 0.00140 | -0.00683 | -0.00344 | -0.00420 |
| **Housing** | | | | | | | |
| % Homeowners | -0.01624 | -0.14609 | -0.00539 | -0.01459 | 0.05641 | -0.02596 | -0.13894 |
| % Vacant Units | 0.41776** | -0.33160 | -0.19233 | 0.29842 | -0.52737 | -0.08742 | -0.14256 |
| **Time Varying** | | | | | | | |
| Logged Population | -0.00178 | 2.25991 | 3.47209* | 1.59609 | -0.85030 | 0.85865 | 3.96082 |
| % Young People | -0.11742 | -0.28351 | -0.01448 | -0.10966 | 0.18194 | -0.36857 | -0.05107 |
| Ethnic Heterogeneity | 0.00363 | -0.17775 | 0.03825 | 0.03941 | -0.02723 | 0.02021 | -0.02990 |
| % Low-income | 0.07596 | -0.04994 | 0.05310 | -0.02743 | 0.01676 | 0.12100 | -0.03378 |
| Intercept | -17.41156 | -30.05996 | -54.04462** | -40.00890* | -21.23945 | -23.56213 | -45.27670 |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .64: Los Angeles: Spring Homicide

| | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00460 | 0.16344 | 0.00947 | -0.02457 | -0.07668 | -0.02481 | 0.02156 |
| % Residential LU | -0.00548 | 0.13694 | -0.01090 | -0.01789 | -0.00448 | -0.00568 | 0.00632 |
| % Retail LU | 0.00798 | 0.17226 | 0.01110 | -0.01445 | -0.03634 | 0.00038 | 0.00640 |
| % Office LU | -0.04657 | 0.14987 | -0.00151 | -0.02454 | 0.00572 | -0.02030 | 0.00663 |
| % School LU | -0.02706 | | -0.00520 | -0.16707 | | -0.01504 | -0.03034 |
| # of bars | | | 0.10129 | -0.36313 | | | 1.80603** |
| # of grocery stores | 0.23495 | 0.49682 | -0.39097 | -0.25807 | -0.01521 | -0.66544 | -0.29578 |
| # of restaurants | 0.03839 | -1.29759 | 0.06334 | 0.35469** | 0.21756 | -0.01300 | 0.11650 |
| **Housing** | | | | | | | |
| % Homeowners | -0.00608 | 0.01226 | 0.00032 | 0.00108 | 0.00279 | -0.01688 | -0.01736 |
| % Vacant Units | 0.01641 | 0.04942 | 0.00047 | 0.02042 | 0.00618 | -0.02281 | 0.01360 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.63024** | 1.99494*** | 0.60153*** | 0.72370** | 0.72122** | 0.25998 | 0.90084*** |
| % Young People | -0.00930 | -0.04149 | 0.00513 | -0.00380 | 0.04079 | 0.00682 | -0.00468 |
| Ethnic Heterogeneity | 0.00041 | -0.02561 | -0.00810 | -0.01238 | -0.02482 | 0.00012 | 0.00841 |
| % Low-income | 0.00862 | 0.00296 | -0.00430 | 0.00603 | 0.03163* | -0.02063 | 0.00170 |

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Table .64 – *Continued from previous page*

| | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.07033 | -0.02091 | -0.02080 | 0.05810 | 0.07554 | 0.06845 | -0.05248 |
| % Residential LU | 0.02514 | 0.02979 | -0.01428 | 0.01635 | 0.06356 | 0.00716 | -0.06828 |
| % Retail LU | 0.44587*** | -0.28878 | -0.07613 | 0.00352 | -0.20290 | -0.08177 | -0.20115 |
| % Office LU | -0.06802 | -0.27072 | 0.07298 | -0.16462 | 0.06820 | -0.12035 | 0.06006 |
| % School LU | 0.06093 | -0.46054 | -0.35485* | -0.00236 | -0.17165 | 0.18920 | -0.43715* |
| # of bars | 0.01447 | 0.01829 | -0.01188 | 0.02608 | 0.01961 | -0.05443 | 0.01125 |
| # of grocery stores | -0.00506 | -0.01480 | -0.00647 | -0.00379 | 0.01442 | -0.00030 | -0.00835 |
| # of restaurants | -0.00313 | 0.00509 | -0.00148 | -0.00070 | -0.00700 | 0.00238 | -0.00082 |
| **Housing** | | | | | | | |
| % Homeowners | 0.05041 | 0.00144 | 0.02284 | 0.01837 | -0.05064 | 0.00593 | 0.11506* |
| % Vacant Units | -0.34991 | -0.08491 | -0.30354 | 0.34700 | 0.27990 | 0.05419 | 0.25177 |
| **Time Varying** | | | | | | | |
| Logged Population | 2.13484 | 1.03672 | 2.95704 | 1.30813 | -0.72410 | 2.32426 | 5.41553* |
| % Young People | -0.16529 | -0.48052 | -0.05337 | -0.02856 | -0.04970 | -0.07369 | -0.44810* |
| Ethnic Heterogeneity | -0.00052 | -0.00970 | 0.01568 | -0.01043 | 0.02440 | -0.01430 | -0.03566 |
| % Low-income | 0.03747 | 0.21960* | 0.13762* | 0.01816 | -0.00275 | -0.01164 | 0.13942 |
| Intercept | -44.24859* | -42.34180 | -50.01219** | -34.93168 | -10.76210 | -38.72501 | -73.87017** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: LU = Land Use. Table is unstandardized coefficients.*

Table .65: Los Angeles: Summer Homicide

| | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|
| | 7am-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | |
| % Industrial LU | 0.01458 | 0.01184 | -0.02772 | -0.04990 | 0.00844 | -0.02441 |
| % Residential LU | 0.01128 | -0.00421 | -0.01408 | 0.00914 | -0.00635 | -0.00030 |
| % Retail LU | 0.02570 | 0.00559 | 0.00734 | 0.02458 | 0.01019 | 0.01435 |
| % Office LU | 0.00909 | -0.00305 | -0.03081 | -0.17989 | -0.03189 | 0.00031 |
| % School LU | | 0.00022 | -0.00979 | | -0.04572 | |
| # of bars | -0.54014 | 0.27608 | | 2.86359*** | 0.27121 | |
| # of grocery stores | 0.37460 | -0.16560 | 0.23550 | 0.93239* | 0.36148 | -0.18170 |
| # of restaurants | -0.00754 | -0.04755 | 0.03290 | 0.20704 | -0.45659 | 0.06387 |
| **Housing** | | | | | | |
| % Homeowners | -0.01605* | -0.01049 | -0.02222* | 0.00554 | -0.00580 | -0.00391 |
| % Vacant Units | 0.00742 | -0.01731 | 0.00321 | 0.06749* | 0.03539* | 0.01550 |
| **Time Varying** | | | | | | |
| Logged Population | 0.59765** | 0.88472*** | 0.58865** | 1.11510** | 0.77528*** | 0.85247** |
| % Young People | 0.00784 | -0.01070 | 0.01975 | -0.06717 | 0.01796 | 0.01693 |
| Ethnic Heterogeneity | 0.02242 | -0.00839 | -0.01736 | 0.02100 | -0.01082 | 0.00874 |
| % Low-income | 0.00212 | -0.01025 | 0.00686 | 0.03966* | 0.00862 | 0.01705 |

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Table .65 – *Continued from previous page*

| | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|
| | 7am-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | |
| **Land Use and Business** | | | | | | |
| % Industrial LU | -0.00307 | -0.00580 | 0.02762 | -0.00576 | 0.01290 | 0.07322 |
| % Residential LU | -0.01810 | -0.03996 | 0.04628 | -0.08706 | 0.03427 | -0.02287 |
| % Retail LU | -0.18156 | 0.18507 | -0.20492 | -0.46586 | -0.24983 | 0.24896 |
| % Office LU | -0.04417 | -0.28347* | 0.19431 | -0.22494 | -0.03417 | -0.20356 |
| % School LU | -0.23766 | -0.10503 | -0.09286 | -0.04614 | 0.04050 | 0.06344 |
| # of bars | 0.02870 | -0.04740 | 0.03933 | -0.02208 | 0.02478 | 0.01458 |
| # of grocery stores | 0.00774 | -0.00868 | 0.00866 | 0.01353 | 0.01809** | -0.01526 |
| # of restaurants | -0.00354 | 0.00107 | -0.00556 | -0.00295 | -0.00069 | -0.00084 |
| **Housing** | | | | | | |
| % Homeowners | 0.12151*** | 0.02985 | 0.03430 | -0.00827 | 0.02295 | 0.05537 |
| % Vacant Units | 0.23406 | 0.15376 | -0.11865 | 0.40691 | -0.14901 | 0.11755 |
| **Time Varying** | | | | | | |
| Logged Population | 2.63826* | 1.80197 | 0.71675 | 4.82516 | -0.77301 | 4.49733 |
| % Young People | -0.01049 | -0.04353 | -0.13065 | -0.25584 | -0.03516 | -0.38504* |
| Ethnic Heterogeneity | 0.04935 | 0.02566 | 0.02043 | -0.02018 | 0.02379 | -0.01136 |
| % Low-income | 0.13480** | 0.07763 | 0.14914* | -0.09829 | 0.04511 | 0.05038 |
| Intercept | -59.80875*** | -39.21956* | -28.45872 | -63.71610 | -10.73672 | -67.57473* |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .66: Los Angeles: Fall Homicide

| | 21 | 22 | 23 | 24 | 25 | 26 | 27 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00227 | -0.00357 | -0.00431 | -0.06683 | -0.14930 | 0.01354 | -0.02684 |
| % Residential LU | -0.00020 | -0.00445 | -0.00790 | 0.01584 | 0.01990 | -0.00028 | -0.00565 |
| % Retail LU | -0.00708 | -0.01417 | 0.01421 | 0.02306 | 0.01546 | 0.02247 | 0.02253 |
| % Office LU | 0.01587 | 0.00374 | -0.02574 | -0.01788 | -0.09800 | 0.00117 | -0.00796 |
| % School LU | -0.00545 | 0.01301 | -0.00997 | 0.03343 | | 0.01780 | 0.01266 |
| # of bars | | 1.35072 | 0.12169 | 1.04603 | | | |
| # of grocery stores | 0.60456 | 0.70232 | 0.24342 | -0.40420 | 0.70210 | 0.35076 | -0.15444 |
| # of restaurants | -0.00639 | 0.08255 | -0.08908 | -0.12824 | 0.04555 | 0.07754 | -0.00716 |
| **Housing** | | | | | | | |
| % Homeowners | -0.02060* | -0.01500 | -0.01502 | -0.01525 | 0.00317 | -0.00583 | -0.00863 |
| % Vacant Units | 0.01145 | 0.00598 | -0.03939 | 0.03674 | 0.06114 | -0.02428 | 0.04178* |
| **Time Varying** | | | | | | | |
| Logged Population | 0.46985* | 0.77924* | 0.66423** | 1.18188*** | 0.78585 | 0.85686*** | 0.73436*** |
| % Young People | 0.03203* | 0.01229 | -0.02669 | -0.04716 | -0.04138 | 0.02653 | 0.02569 |
| Ethnic Heterogeneity | -0.01617 | -0.03567 | 0.00117 | 0.01846 | 0.03230 | -0.01402 | 0.00578 |
| % Low-income | -0.00359 | 0.04606** | 0.01701 | 0.00191 | 0.00244 | -0.00501 | -0.01326 |

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Table .66 – *Continued from previous page*

| | 21 | 22 | 23 | 24 | 25 | 26 | 27 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.02716 | 0.04593 | 0.01062 | 0.07312 | 0.11901* | 0.07912 | -0.06618 |
| % Residential LU | 0.00403 | 0.02612 | -0.00777 | 0.01330 | -0.06154 | -0.00838 | -0.04442 |
| % Retail LU | 0.10571 | 0.28125 | -0.12704 | 0.26132 | -0.34576 | -0.14050 | -0.15807 |
| % Office LU | 0.06346 | -0.11578 | -0.00394 | -0.34895 | -0.34043 | 0.24789 | 0.01966 |
| % School LU | -0.01617 | -0.14983 | 0.00508 | 0.02903 | 0.49165** | -0.13306 | -0.37929* |
| # of bars | -0.04006 | -0.11680 | 0.03464 | -0.01246 | 0.04981 | 0.04716* | -0.01507 |
| # of grocery stores | 0.00241 | -0.02718 | -0.00115 | -0.00921 | 0.02686 | -0.00148 | -0.00636 |
| # of restaurants | -0.00097 | 0.00702 | 0.00010 | 0.00324 | -0.00333 | -0.00588* | -0.00355 |
| **Housing** | | | | | | | |
| % Homeowners | 0.08602 | -0.01670 | 0.06456 | 0.05368 | 0.00971 | 0.10000* | 0.01235 |
| % Vacant Units | 0.10902 | 0.60444 | -0.21131 | 0.35427 | 0.09240 | 0.12899 | -0.26785 |
| **Time Varying** | | | | | | | |
| Logged Population | 2.54255 | -0.09418 | 2.07692 | 1.00780 | 0.92148 | 5.54996** | 3.46909 |
| % Young People | -0.31532* | -0.26361 | -0.18812 | 0.01362 | -0.04889 | -0.23593 | -0.18034 |
| Ethnic Heterogeneity | 0.00972 | -0.01399 | -0.00839 | -0.01801 | 0.14215* | 0.04367 | -0.03621 |
| % Low-income | 0.06337 | 0.00732 | 0.10362 | 0.01588 | 0.03173 | 0.09085 | 0.09149 |
| Intercept | -47.19172** | -15.09504 | -39.54236* | -39.92140 | -38.80725 | -87.41547*** | -46.56270* |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .67: Los Angeles: Winter Larceny

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00311* | -0.00035 | 0.00435** | 0.00484* | 0.00342 | 0.00330 | -0.00104 |
| % Residential LU | -0.00755*** | -0.00657*** | -0.00684*** | -0.00570*** | -0.01281*** | -0.00712*** | -0.00716*** |
| % Retail LU | 0.00697*** | 0.01182*** | 0.00906*** | 0.00438** | 0.01090*** | 0.00732*** | 0.00761** |
| % Office LU | -0.00232 | -0.00158 | 0.00156 | 0.00172 | 0.00228 | 0.00163 | -0.00149 |
| % School LU | -0.00740*** | 0.00848*** | -0.00066 | -0.00340 | -0.00277 | -0.00008 | -0.00043 |
| # of bars | -0.04611 | -0.14133 | 0.05444 | 0.31837** | 0.00984 | 0.23323* | 0.06535 |
| # of grocery stores | 0.17597*** | 0.32009*** | 0.24897*** | 0.10800 | 0.30718*** | 0.23446*** | 0.14168 |
| # of restaurants | 0.09519*** | 0.12447*** | 0.14665*** | 0.09589*** | 0.16341*** | 0.14418*** | 0.09241** |
| **Housing** | | | | | | | |
| % Homeowners | 0.00018 | 0.00015 | -0.00244*** | -0.00258** | -0.00178 | -0.00403*** | -0.00283 |
| % Vacant Units | 0.00592** | 0.00274 | 0.00364 | 0.00413 | 0.00205 | 0.00651* | 0.01271** |
| **Time Varying** | | | | | | | |
| Logged Population | 0.65636*** | 0.65273*** | 0.63632*** | 0.60178*** | 0.51846*** | 0.61428*** | 0.61309*** |
| % Young People | 0.00700*** | 0.00777*** | -0.00164 | 0.00388 | 0.00609** | 0.00203 | 0.00532 |
| Ethnic Heterogeneity | 0.00271** | 0.00055 | 0.00453*** | 0.00678*** | 0.00205 | 0.00420*** | 0.00827** |
| % Low-income | -0.00034 | -0.00350* | -0.00353*** | -0.00292* | -0.00456** | -0.00335* | -0.00487 |

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Table .67 – *Continued from previous page*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.00952** | 0.01040 | 0.00344 | -0.00621 | 0.01029* | 0.00949* | 0.01948* |
| % Residential LU | 0.01162*** | 0.01764*** | 0.01677*** | 0.01771*** | 0.02146*** | 0.01604*** | 0.02787*** |
| % Retail LU | 0.00035 | -0.00332 | -0.00727 | -0.01372 | 0.01841 | 0.00528 | -0.04890 |
| % Office LU | 0.00681 | 0.01717 | 0.02638** | 0.03556** | 0.00973 | 0.02043 | 0.06467** |
| % School LU | -0.00157 | -0.00988 | -0.00623 | -0.03001* | 0.00790 | -0.04139** | -0.05494* |
| # of bars | 0.00049 | -0.00218 | 0.00421** | 0.01149*** | 0.00555* | 0.00773*** | 0.02074*** |
| # of grocery stores | -0.00075 | -0.00159 | -0.00029 | 0.00152 | -0.00018 | -0.00045 | 0.00079 |
| # of restaurants | 0.00005 | 0.00060 | -0.00036 | -0.00103*** | -0.00049 | -0.00025 | -0.00099* |
| **Housing** | | | | | | | |
| % Homeowners | -0.00521 | -0.01790*** | -0.01594*** | -0.01023** | -0.00998* | -0.00590 | -0.00252 |
| % Vacant Units | 0.02126 | -0.00554 | -0.04699** | -0.04816* | 0.01116 | -0.02701 | -0.00481 |
| **Time Varying** | | | | | | | |
| Logged Population | -0.17979* | -0.60246*** | -0.40922*** | -0.54272*** | -0.67619*** | -0.37148** | -0.57385* |
| % Young People | -0.00483 | 0.00774 | 0.01566** | 0.01687* | 0.00275 | 0.02112** | 0.01746 |
| Ethnic Heterogeneity | -0.00234 | -0.00554 | -0.00222 | -0.00299 | -0.00097 | -0.00454* | -0.00283 |
| % Low-income | -0.00056 | 0.00718 | -0.00204 | 0.01121* | 0.01309* | -0.00184 | 0.02608** |
| Intercept | -9.85975*** | -4.58924** | -6.20169*** | -6.33660*** | -3.99429* | -7.09669*** | -7.81889** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .68: Los Angeles: Spring Larceny

| | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00474*** | -0.00445 | 0.00127 | 0.00431* | 0.00041 | 0.00365* | 0.00162 |
| % Residential LU | -0.00893*** | -0.00799*** | -0.00778*** | -0.00446*** | -0.01438*** | -0.00709*** | -0.00526** |
| % Retail LU | 0.00592*** | 0.01067*** | 0.00803*** | 0.00277 | 0.00602*** | 0.00753*** | 0.00666* |
| % Office LU | -0.00185 | -0.00245 | 0.00157 | 0.00293 | -0.00261 | 0.00100 | 0.00280 |
| % School LU | -0.00614*** | 0.00380 | 0.00157 | 0.00241 | -0.00027 | -0.00226 | -0.00268 |
| # of bars | -0.02672 | -0.12269 | 0.05024 | 0.35160*** | 0.08809 | 0.27233** | 0.39516* |
| # of grocery stores | 0.20893*** | 0.26983*** | 0.20390*** | 0.07079 | 0.27904*** | 0.20399*** | 0.15840 |
| # of restaurants | 0.09220*** | 0.08006*** | 0.14260*** | 0.09672*** | 0.18794*** | 0.14590*** | 0.09181** |
| **Housing** | | | | | | | |
| % Homeowners | -0.00020 | 0.00181 | -0.00329*** | -0.00447*** | -0.00207* | -0.00128 | -0.00267 |
| % Vacant Units | 0.00750*** | -0.00093 | 0.00580** | 0.00460 | -0.00368 | 0.00729** | 0.00803 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.62237*** | 0.70187*** | 0.59542*** | 0.59258*** | 0.49448*** | 0.59167*** | 0.55809*** |
| % Young People | 0.00681*** | 0.00980*** | 0.00162 | 0.00293 | 0.00250 | 0.00854*** | 0.01256*** |
| Ethnic Heterogeneity | 0.00231* | 0.00260 | 0.00368*** | 0.00645*** | 0.00162 | 0.00250* | 0.00470* |
| % Low-income | -0.00102 | -0.00096 | -0.00355*** | -0.00094 | -0.00461** | -0.00315* | -0.00376 |

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Table .68 – *Continued from previous page*

| | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.00985** | 0.01596** | 0.00315 | 0.00978* | 0.00678 | 0.00376 | -0.00426 |
| % Residential LU | 0.01062*** | 0.01544*** | 0.01487*** | 0.02009*** | 0.01279*** | 0.01676*** | 0.01203* |
| % Retail LU | 0.01916 | 0.01942 | -0.01988* | -0.01818 | 0.01534 | -0.01879 | -0.04703 |
| % Office LU | -0.00540 | -0.01519 | 0.02795** | 0.02060 | -0.00937 | 0.02834* | 0.07345*** |
| % School LU | 0.01624 | -0.01469 | -0.01186 | -0.03720** | -0.01140 | -0.02110 | -0.06075* |
| # of bars | 0.00030 | -0.00161 | 0.00564*** | 0.01037*** | 0.00416 | 0.00985*** | 0.01914*** |
| # of grocery stores | -0.00103 | -0.00166 | 0.00037 | 0.00065 | -0.00088 | 0.00076 | 0.00304 |
| # of restaurants | -0.00011 | 0.00019 | -0.00066*** | -0.00033 | -0.00028 | -0.00091*** | -0.00205*** |
| **Housing** | | | | | | | |
| % Homeowners | -0.00931*** | -0.01579*** | -0.01562*** | -0.00315 | -0.01141** | -0.01328*** | -0.00393 |
| % Vacant Units | 0.05048*** | 0.06675** | -0.04060** | -0.00006 | 0.03674 | -0.01330 | 0.03349 |
| **Time Varying** | | | | | | | |
| Logged Population | -0.26201*** | -0.39855** | -0.29726** | -0.50844*** | -0.43308** | -0.36107** | -0.32647 |
| % Young People | -0.00773 | -0.01279 | 0.00856 | 0.01634* | 0.00340 | 0.00975 | 0.03603** |
| Ethnic Heterogeneity | -0.00073 | -0.00079 | -0.00181 | 0.00128 | -0.00166 | 0.00018 | 0.00562 |
| % Low-income | 0.00191 | -0.00080 | -0.00279 | 0.01068* | 0.00803 | 0.00535 | 0.01668 |
| Intercept | -8.60249*** | -7.21932*** | -6.85177*** | -7.69497*** | -5.58643*** | -7.12801*** | -10.14755*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: LU = Land Use. Table is unstandardized coefficients.*

Table .69: Los Angeles: Summer Larceny

| | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|
| | 7am-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | |
| % Industrial LU | -0.00221 | 0.00176 | 0.00319 | -0.00068 | 0.00572** | 0.00171 |
| % Residential LU | -0.00778*** | -0.00772*** | -0.00620*** | -0.01304*** | -0.00740*** | -0.00703*** |
| % Retail LU | 0.00741*** | 0.00816*** | 0.00339* | 0.00958*** | 0.00970*** | 0.00597* |
| % Office LU | -0.00121 | 0.00112 | -0.00028 | 0.00129 | 0.00320 | -0.00047 |
| % School LU | -0.00907*** | -0.00217 | -0.00353 | -0.00308 | -0.00005 | -0.01479** |
| # of bars | -0.10172 | 0.10671 | 0.33507*** | 0.07546 | 0.26493** | 0.39770** |
| # of grocery stores | 0.19595*** | 0.21122*** | 0.11238* | 0.27408*** | 0.24463*** | 0.19814* |
| # of restaurants | 0.11031*** | 0.15974*** | 0.09506*** | 0.15992*** | 0.14250*** | 0.08288** |
| **Housing** | | | | | | |
| % Homeowners | -0.00092 | -0.00324*** | -0.00386*** | -0.00287** | -0.00282*** | -0.00487** |
| % Vacant Units | 0.00517** | 0.00520* | 0.01037*** | 0.00608* | 0.01073*** | 0.01491*** |
| **Time Varying** | | | | | | |
| Logged Population | 0.62789*** | 0.58861*** | 0.60680*** | 0.50981*** | 0.53104*** | 0.60562*** |
| % Young People | 0.00501*** | -0.00045 | -0.00034 | -0.00154 | 0.00185 | 0.00440 |
| Ethnic Heterogeneity | 0.00334*** | 0.00305*** | 0.00647*** | 0.00381** | 0.00398** | 0.00326 |
| % Low-income | -0.00093 | -0.00420*** | -0.00268* | -0.00387* | -0.00486*** | -0.00053 |

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Table .69 – *Continued from previous page*

| | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|
| | 7am-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | |
| **Land Use and Business** | | | | | | |
| % Industrial LU | 0.01189*** | 0.00345 | 0.00192 | 0.00348 | 0.00343 | 0.00484 |
| % Residential LU | 0.01303*** | 0.01790*** | 0.01347*** | 0.01894*** | 0.01462*** | 0.01501* |
| % Retail LU | 0.00036 | -0.02160* | -0.01684 | 0.02497 | -0.00579 | -0.08074** |
| % Office LU | 0.00647 | 0.01912* | 0.01558 | -0.00765 | 0.01716 | 0.03936 |
| % School LU | 0.00628 | -0.01517 | -0.00798 | 0.00102 | 0.00484 | -0.00859 |
| # of bars | 0.00140 | 0.00194 | 0.01152*** | -0.00087 | 0.00739*** | 0.01750*** |
| # of grocery stores | -0.00000 | -0.00052 | 0.00148 | -0.00182 | -0.00109 | 0.00143 |
| # of restaurants | -0.00029 | -0.00018 | -0.00079** | 0.00014 | -0.00047 | -0.00064 |
| **Housing** | | | | | | |
| % Homeowners | -0.01041*** | -0.01796*** | -0.00516 | -0.00867* | -0.01452*** | 0.00538 |
| % Vacant Units | 0.06474*** | -0.01483 | 0.01162 | 0.04572* | -0.05503** | 0.03457 |
| **Time Varying** | | | | | | |
| Logged Population | -0.27168*** | -0.40988*** | -0.22888 | -0.73077*** | -0.39791** | -0.20157 |
| % Young People | -0.00662 | 0.01293* | 0.01404* | 0.01268 | 0.02006** | 0.02199 |
| Ethnic Heterogeneity | -0.00311 | -0.00099 | -0.00192 | -0.00469 | -0.00141 | 0.00397 |
| % Low-income | -0.00093 | -0.00177 | -0.00135 | 0.01949*** | 0.00721 | 0.01734* |
| Intercept | -8.44927*** | -5.79652*** | -9.89532*** | -3.28229* | -6.11443*** | -11.77858*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .70: Los Angeles: Fall Larceny

| | 21 | 22 | 23 | 24 | 25 | 26 | 27 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00179 | -0.00063 | 0.00038 | 0.00421* | 0.00327 | 0.00407* | -0.00239 |
| % Residential LU | -0.00887*** | -0.00822*** | -0.00811*** | -0.00556*** | -0.01327*** | -0.00803*** | -0.00758*** |
| % Retail LU | 0.00560*** | 0.01115*** | 0.00864*** | 0.00200 | 0.00864*** | 0.00805*** | 0.00572* |
| % Office LU | -0.00427** | -0.00205 | -0.00014 | 0.00050 | -0.00110 | 0.00085 | -0.00026 |
| % School LU | -0.00546*** | 0.00636** | 0.00276 | -0.00090 | -0.00418 | 0.00142 | -0.00349 |
| # of bars | -0.00545 | 0.19347 | 0.14218 | 0.27501** | 0.20526 | 0.23406* | 0.35353* |
| # of grocery stores | 0.21529*** | 0.32880*** | 0.23288*** | 0.18348*** | 0.34140*** | 0.22792*** | 0.23048** |
| # of restaurants | 0.10115*** | 0.03678 | 0.16657*** | 0.09981*** | 0.17565*** | 0.14730*** | 0.05412 |
| **Housing** | | | | | | | |
| % Homeowners | -0.00139* | 0.00219* | -0.00165** | -0.00250** | -0.00320*** | -0.00262** | -0.00685*** |
| % Vacant Units | 0.00460* | 0.00239 | 0.00347 | 0.01131*** | 0.00208 | 0.00549* | 0.01026* |
| **Time Varying** | | | | | | | |
| Logged Population | 0.61780*** | 0.73987*** | 0.58804*** | 0.59720*** | 0.47771*** | 0.58164*** | 0.50748*** |
| % Young People | 0.00689*** | 0.01191*** | 0.00458** | 0.00802*** | 0.00094 | 0.00511* | 0.00871* |
| Ethnic Heterogeneity | 0.00320** | 0.00044 | 0.00529*** | 0.00398** | 0.00391** | 0.00276* | 0.00954*** |
| % Low-income | -0.00094 | -0.00061 | -0.00435*** | -0.00270* | -0.00720*** | -0.00383** | -0.00150 |

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Table .70 – *Continued from previous page*

| | 21 | 22 | 23 | 24 | 25 | 26 | 27 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.00981** | 0.02197*** | 0.00767* | 0.00629 | 0.01093* | 0.00698 | 0.00113 |
| % Residential LU | 0.01283*** | 0.01677*** | 0.01543*** | 0.01767*** | 0.01884*** | 0.01299*** | 0.01206* |
| % Retail LU | 0.01648 | -0.01451 | -0.00761 | -0.03027* | 0.02068 | -0.01024 | -0.00368 |
| % Office LU | 0.01597 | 0.00576 | 0.01987* | 0.01537 | 0.02648 | 0.00256 | -0.00383 |
| % School LU | 0.03637*** | 0.02838 | -0.00385 | 0.00175 | 0.01320 | 0.02262 | -0.03434 |
| # of bars | 0.00173 | 0.00316 | 0.00293 | 0.01323*** | 0.00114 | 0.01388*** | 0.01825*** |
| # of grocery stores | -0.00031 | -0.00031 | -0.00076 | 0.00149 | 0.00018 | -0.00031 | -0.00025 |
| # of restaurants | -0.00061** | 0.00009 | -0.00021 | -0.00055* | -0.00043 | -0.00083*** | -0.00074 |
| **Housing** | | | | | | | |
| % Homeowners | -0.01101*** | -0.01404** | -0.01338*** | -0.00893** | -0.01320*** | -0.00696* | 0.00917 |
| % Vacant Units | 0.08100*** | 0.04814 | 0.01698 | 0.00318 | 0.02397 | 0.01798 | 0.01396 |
| **Time Varying** | | | | | | | |
| Logged Population | -0.31759*** | -0.65380*** | -0.35573*** | -0.64921*** | -0.72505*** | -0.27840* | -0.36870 |
| % Young People | -0.01289 | 0.00750 | 0.00977 | 0.01308 | 0.02826*** | 0.00053 | 0.03142* |
| Ethnic Heterogeneity | -0.00407 | 0.00577 | -0.00450** | 0.00140 | -0.00431 | 0.00077 | -0.00027 |
| % Low-income | -0.00178 | 0.00379 | -0.00049 | 0.00865 | 0.00953 | 0.00641 | 0.02025* |
| Intercept | -7.83787*** | -5.62606*** | -6.89064*** | -5.61921*** | -3.15178* | -8.12453*** | -9.54930*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .71: Los Angeles: Winter Motor Theft

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.00005 | 0.00450 | 0.00498* | 0.00492 | 0.00690* | 0.00403 | 0.00891 |
| % Residential LU | -0.00510*** | -0.00205 | 0.00008 | -0.00204 | -0.00643** | -0.00411** | 0.00104 |
| % Retail LU | 0.00106 | 0.00275 | 0.00681*** | 0.00225 | 0.00683* | 0.00474* | 0.00114 |
| % Office LU | -0.00132 | -0.00531 | 0.00211 | 0.00103 | 0.00045 | -0.00131 | 0.00343 |
| % School LU | -0.01484*** | -0.00643 | -0.00335 | -0.00003 | 0.00182 | -0.00502 | 0.00174 |
| # of bars | -0.13884 | 0.13995 | 0.13875 | 0.20209 | -0.01041 | 0.39155** | 0.13405 |
| # of grocery stores | 0.10442 | 0.07437 | 0.09568* | -0.02494 | 0.10383 | 0.02945 | 0.13177 |
| # of restaurants | 0.04412 | 0.06235 | 0.07771*** | 0.07221* | 0.14859*** | 0.06077* | 0.11270* |
| **Housing** | | | | | | | |
| % Homeowners | -0.00716*** | -0.00522** | -0.00638*** | -0.00471*** | -0.00622*** | -0.00600*** | -0.00993*** |
| % Vacant Units | -0.00250 | -0.00541 | 0.00279 | 0.01014* | -0.00105 | 0.00306 | 0.01185 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.56203*** | 0.70711*** | 0.67653*** | 0.62700*** | 0.51803*** | 0.58514*** | 0.53307*** |
| % Young People | 0.00486* | 0.00255 | 0.00291 | -0.00188 | 0.00416 | 0.00431 | -0.00126 |
| Ethnic Heterogeneity | 0.00451** | 0.00471 | 0.00070 | 0.00319 | 0.00199 | -0.00053 | 0.00361 |
| % Low-income | -0.00286* | 0.00270 | -0.00252 | -0.00314 | -0.00083 | -0.00409* | -0.00253 |

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Table .71 – *Continued from previous page*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.01167* | 0.01385 | 0.00933* | 0.01033 | 0.01939** | 0.00999* | 0.02059 |
| % Residential LU | -0.00056 | 0.00479 | -0.00400 | 0.00452 | 0.01000 | -0.00237 | 0.00722 |
| % Retail LU | -0.01236 | 0.02264 | 0.01859 | -0.03033 | 0.01649 | 0.00918 | -0.04335 |
| % Office LU | -0.01971 | 0.00328 | -0.02860* | -0.04222* | -0.03192 | -0.00997 | 0.02935 |
| % School LU | -0.00500 | -0.00594 | -0.00359 | -0.01042 | 0.00068 | -0.01537 | 0.01377 |
| # of bars | -0.00003 | -0.00144 | 0.00352 | 0.00841* | 0.00431 | 0.00609* | 0.01360* |
| # of grocery stores | -0.00022 | -0.00104 | -0.00109 | -0.00292* | -0.00196 | -0.00236* | -0.00037 |
| # of restaurants | -0.00076 | 0.00020 | -0.00115*** | -0.00050 | -0.00098 | -0.00087* | -0.00193* |
| **Housing** | | | | | | | |
| % Homeowners | 0.00487 | -0.01246 | -0.00314 | 0.00115 | -0.00794 | 0.00367 | -0.00562 |
| % Vacant Units | 0.01878 | -0.06785 | -0.06883*** | -0.09092** | -0.07923* | -0.12125*** | -0.08298 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.26357 | -0.47573* | 0.73849*** | 0.45587* | 0.25159 | 0.53069** | 0.50248 |
| % Young People | -0.00615 | -0.02403 | -0.03851*** | -0.02034 | -0.01571 | -0.00640 | -0.04984 |
| Ethnic Heterogeneity | -0.00137 | -0.00942 | -0.00440 | -0.00448 | -0.01062* | -0.00064 | -0.00530 |
| % Low-income | 0.03875*** | 0.03008*** | 0.01097* | 0.03568*** | 0.01838 | 0.03410*** | 0.02720* |
| Intercept | -16.09609*** | -6.64864* | -19.12217*** | -17.83515*** | -14.09017*** | -17.41400*** | -17.31645*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .72: Los Angeles: Spring Motor Theft

| | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.00309 | 0.00133 | 0.00397* | 0.00290 | 0.00827** | 0.00399 | 0.00515 |
| % Residential LU | -0.00419** | -0.00377 | -0.00283* | -0.00164 | -0.00664** | -0.00414** | -0.00152 |
| % Retail LU | 0.00474* | 0.00512 | 0.00440** | 0.00407 | 0.00482 | 0.00625** | 0.00893* |
| % Office LU | 0.00261 | -0.00229 | 0.00028 | 0.00028 | 0.00194 | -0.00017 | -0.00080 |
| % School LU | -0.00812** | -0.01068 | 0.00137 | -0.00090 | 0.00494 | -0.00162 | -0.00325 |
| # of bars | -0.32046 | -0.25381 | -0.19293 | 0.07988 | -0.12990 | 0.04308 | 0.11524 |
| # of grocery stores | 0.16168* | 0.05512 | 0.15866*** | -0.08954 | 0.11615 | 0.05985 | 0.12484 |
| # of restaurants | 0.03090 | 0.06605 | 0.09035*** | 0.05962* | 0.10846** | 0.08348*** | -0.01702 |
| **Housing** | | | | | | | |
| % Homeowners | -0.00519*** | -0.00487** | -0.00470*** | -0.00386** | -0.00734*** | -0.00380** | -0.00728** |
| % Vacant Units | 0.00204 | 0.00455 | 0.00161 | -0.00002 | 0.00548 | 0.00901* | 0.00282 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.53205*** | 0.67269*** | 0.69844*** | 0.66791*** | 0.49492*** | 0.68291*** | 0.61728*** |
| % Young People | 0.00467* | 0.00735 | 0.00274 | 0.00815* | 0.00054 | 0.00180 | 0.00636 |
| Ethnic Heterogeneity | 0.00120 | 0.00413 | 0.00181 | 0.00361* | -0.00131 | 0.00091 | 0.00332 |
| % Low-income | -0.00167 | -0.00131 | -0.00358** | -0.00516** | 0.00076 | -0.00047 | 0.00131 |

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Table .72 – *Continued from previous page*

| | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.02109*** | 0.02716** | 0.01800*** | 0.01414** | 0.02102** | 0.01788*** | 0.01006 |
| % Residential LU | 0.01107** | 0.01208* | -0.00090 | 0.00436 | 0.00973 | 0.00209 | 0.00228 |
| % Retail LU | 0.00194 | -0.00697 | -0.00732 | 0.00735 | 0.04158 | 0.00674 | -0.02319 |
| % Office LU | 0.02606 | 0.01489 | -0.02294 | -0.00366 | -0.00613 | -0.00076 | 0.02064 |
| % School LU | 0.00042 | -0.09815** | -0.01553 | -0.08386*** | -0.05126 | -0.04496* | -0.08697* |
| # of bars | -0.00146 | -0.00522 | 0.00550* | 0.00205 | -0.00290 | 0.00664* | 0.01039 |
| # of grocery stores | 0.00071 | -0.00333 | -0.00139 | 0.00027 | -0.00088 | -0.00103 | -0.00060 |
| # of restaurants | -0.00073* | 0.00014 | -0.00142*** | -0.00132*** | -0.00068 | -0.00191*** | -0.00180* |
| **Housing** | | | | | | | |
| % Homeowners | -0.00009 | -0.00615 | 0.00392 | 0.00410 | 0.00812 | 0.00519 | 0.01549 |
| % Vacant Units | 0.01252 | -0.08267 | -0.00840 | -0.05126 | -0.04598 | -0.03513 | -0.00639 |
| **Time Varying** | | | | | | | |
| Logged Population | -0.12454 | 0.05149 | 0.92271*** | 0.48087* | 0.35736 | 0.79089*** | 0.76477 |
| % Young People | -0.02494 | 0.00479 | -0.02651** | 0.00873 | 0.00456 | -0.00220 | -0.02888 |
| Ethnic Heterogeneity | -0.00005 | -0.00170 | 0.00166 | 0.00119 | -0.00427 | 0.00327 | -0.00124 |
| % Low-income | 0.04117*** | 0.03096*** | 0.01627*** | 0.02570*** | 0.01568 | 0.02001** | 0.02990* |
| Intercept | -11.92097*** | -13.60544*** | -22.59316*** | -19.47926*** | -16.71131*** | -21.70646*** | -22.37174*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: LU = Land Use. Table is unstandardized coefficients.*

## Table .73: Los Angeles: Summer Motor Theft

| | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|
| | 7am-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | |
| % Industrial LU | 0.00320 | 0.00218 | 0.00445 | 0.00382 | 0.00383 | -0.00123 |
| % Residential LU | -0.00315* | -0.00375*** | -0.00295 | -0.00776*** | -0.00268 | -0.00389 |
| % Retail LU | 0.00370* | 0.00313* | 0.00210 | 0.00524* | 0.00440* | 0.00181 |
| % Office LU | 0.00267 | -0.00034 | -0.00396 | -0.00151 | 0.00005 | -0.00373 |
| % School LU | -0.01448*** | -0.00256 | -0.00160 | -0.00595 | 0.00135 | 0.00007 |
| # of bars | -0.17802 | -0.01292 | 0.19455 | -0.10557 | 0.07423 | 0.02379 |
| # of grocery stores | 0.03186 | 0.03235 | 0.08513 | -0.01971 | 0.08499 | -0.14875 |
| # of restaurants | 0.07150*** | 0.09978*** | 0.06120* | 0.13434*** | 0.05921* | -0.04993 |
| **Housing** | | | | | | |
| % Homeowners | -0.00309** | -0.00548*** | -0.00273* | -0.00679*** | -0.00447*** | -0.00960*** |
| % Vacant Units | 0.00074 | 0.00486 | 0.01062** | 0.00183 | 0.00688 | 0.01248 |
| **Time Varying** | | | | | | |
| Logged Population | 0.61546*** | 0.65462*** | 0.70886*** | 0.49170*** | 0.64195*** | 0.58618*** |
| % Young People | 0.00502** | 0.00227 | 0.00087 | -0.00306 | 0.00817** | 0.01357* |
| Ethnic Heterogeneity | 0.00476*** | 0.00210 | 0.00200 | 0.00436 | 0.00424** | 0.00326 |
| % Low-income | 0.00013 | -0.00035 | -0.00184 | -0.00534* | -0.00062 | -0.00611 |

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Table .73 – *Continued from previous page*

| | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|
| | 7am-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | |
| **Land Use and Business** | | | | | | |
| % Industrial LU | 0.02129*** | 0.01025** | 0.00515 | 0.00835 | 0.01641*** | 0.00845 |
| % Residential LU | 0.01040*** | -0.00470 | -0.00088 | 0.01044 | -0.00145 | 0.00911 |
| % Retail LU | 0.03042 | 0.00546 | -0.02463 | 0.01690 | 0.00928 | -0.00485 |
| % Office LU | 0.00085 | -0.02937* | -0.00945 | -0.04610 | -0.00185 | -0.01999 |
| % School LU | 0.01332 | -0.01836 | -0.02267 | -0.03964 | -0.04057* | 0.01422 |
| # of bars | 0.00192 | 0.00313 | 0.00876** | 0.00104 | 0.00597* | 0.01460* |
| # of grocery stores | 0.00029 | -0.00198* | -0.00034 | -0.00164 | 0.00067 | -0.00026 |
| # of restaurants | -0.00159*** | -0.00139*** | -0.00162*** | -0.00106* | -0.00187*** | -0.00125 |
| **Housing** | | | | | | |
| % Homeowners | -0.00781 | 0.00011 | 0.00470 | -0.00152 | 0.00484 | 0.01401 |
| % Vacant Units | 0.01230 | -0.04672* | -0.06806* | -0.01140 | -0.00709 | -0.05835 |
| **Time Varying** | | | | | | |
| Logged Population | 0.16799 | 0.87512*** | 0.66380** | -0.12800 | 0.92509*** | 0.00803 |
| % Young People | -0.02728* | -0.03578*** | -0.02157 | 0.01481 | -0.01796 | -0.03772 |
| Ethnic Heterogeneity | -0.01028** | 0.00106 | 0.00849** | -0.00380 | -0.00043 | 0.00455 |
| % Low-income | 0.02047*** | 0.01571** | 0.03129*** | 0.04427*** | 0.00550 | 0.05644*** |
| Intercept | -14.49317*** | -20.84048*** | -21.12221*** | -11.16266*** | -22.59582*** | -14.26211** |

$*p < .05; **p < .01; ***p < .001$

*Note:*

Table .74: Los Angeles: Fall Motor Theft

| | 21 | 22 | 23 | 24 | 25 | 26 | 27 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.00444* | 0.00056 | 0.00507** | 0.00463 | 0.00854** | 0.00601* | 0.00263 |
| % Residential LU | -0.00456** | 0.00128 | -0.00262* | -0.00155 | -0.00765*** | -0.00415** | -0.00333 |
| % Retail LU | 0.00343 | 0.00694 | 0.00264 | 0.00848*** | 0.00415 | 0.00214 | 0.00178 |
| % Office LU | -0.00151 | 0.00067 | -0.00028 | -0.00134 | 0.00043 | 0.00171 | -0.00664 |
| % School LU | -0.01232*** | -0.00504 | 0.00186 | 0.00178 | -0.00135 | -0.00285 | 0.00072 |
| # of bars | 0.25019 | -0.57841 | -0.01963 | 0.06219 | 0.13042 | -0.01213 | 0.17090 |
| # of grocery stores | 0.06635 | 0.10380 | 0.01132 | 0.00454 | 0.03222 | 0.04960 | -0.11876 |
| # of restaurants | 0.04442 | 0.12632*** | 0.08119*** | -0.00566 | 0.06846 | 0.14358*** | 0.12997* |
| **Housing** | | | | | | | |
| % Homeowners | -0.00515*** | -0.00894*** | -0.00523*** | -0.00211 | -0.00806*** | -0.00637*** | -0.00495* |
| % Vacant Units | 0.00434 | 0.01305* | 0.00626* | 0.00718 | 0.00207 | 0.00909* | 0.01353 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.59264*** | 0.66805*** | 0.66743*** | 0.75617*** | 0.49726*** | 0.61356*** | 0.54777*** |
| % Young People | 0.00308 | 0.00334 | 0.00299 | 0.00575 | 0.00412 | -0.00063 | 0.00998 |
| Ethnic Heterogeneity | 0.00204 | 0.00217 | 0.00382** | 0.00327 | 0.00076 | 0.00013 | -0.00085 |
| % Low-income | 0.00065 | -0.00247 | -0.00278* | -0.00243 | -0.00201 | -0.00470** | -0.00393 |

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Table .74 – *Continued from previous page*

| | 21 | 22 | 23 | 24 | 25 | 26 | 27 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.01932*** | 0.03349*** | 0.00966* | 0.00054 | 0.02113** | -0.00070 | -0.00201 |
| % Residential LU | 0.00923* | 0.01161 | -0.00185 | -0.00552 | 0.01728* | -0.00780 | -0.01558 |
| % Retail LU | -0.00809 | -0.06384 | -0.00703 | -0.02252 | 0.02657 | 0.00549 | -0.02492 |
| % Office LU | 0.00066 | -0.00590 | -0.00873 | -0.04002* | -0.01760 | -0.02039 | -0.12816*** |
| % School LU | -0.02053 | 0.06513* | -0.02603* | -0.01190 | -0.02003 | -0.03868* | -0.03007 |
| # of bars | -0.00257 | -0.00308 | 0.00411 | 0.01550*** | 0.00245 | 0.00741* | 0.01348* |
| # of grocery stores | 0.00069 | -0.00088 | -0.00140 | -0.00060 | -0.00190 | 0.00080 | -0.00421 |
| # of restaurants | -0.00140*** | -0.00005 | -0.00147*** | -0.00122** | -0.00107* | -0.00205*** | 0.00008 |
| **Housing** | | | | | | | |
| % Homeowners | -0.00118 | -0.01131 | -0.00085 | 0.00614 | 0.00095 | 0.01161* | 0.01414 |
| % Vacant Units | 0.06054* | -0.05703 | -0.04422* | -0.05858 | 0.03603 | -0.07624** | -0.07474 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.22922 | -0.05811 | 0.77870*** | 0.59628** | -0.13987 | 0.98950*** | 0.80835 |
| % Young People | -0.01810 | -0.07408** | -0.02256* | -0.01678 | -0.00600 | -0.00373 | -0.01899 |
| Ethnic Heterogeneity | -0.00094 | 0.00314 | -0.00138 | 0.00548 | -0.00311 | 0.00442 | 0.00117 |
| % Low-income | 0.02959*** | 0.03095*** | 0.01990*** | 0.02568*** | 0.03792*** | 0.02832*** | 0.04345** |
| Intercept | -15.99018*** | -11.31114*** | -20.28181*** | -20.71578*** | -11.75601*** | -23.10235*** | -21.36851*** |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .75: Los Angeles: Winter Burglary

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00111 | -0.00341 | 0.00747** | 0.00728* | 0.00223 | 0.00407 | 0.00987 |
| % Residential LU | 0.00276* | -0.00529* | -0.00573*** | -0.00323 | -0.01001*** | -0.00932*** | -0.01116** |
| % Retail LU | -0.00371* | -0.00152 | 0.00881*** | 0.01171*** | -0.00379 | 0.00505 | -0.00241 |
| % Office LU | -0.00479* | -0.01356** | 0.00219 | 0.00439 | -0.00152 | -0.00060 | -0.01406* |
| % School LU | -0.01461*** | 0.01129*** | 0.01038*** | 0.00871* | 0.00299 | 0.00826* | 0.00684 |
| # of bars | -0.08066 | 0.25139 | 0.18617 | 0.54445*** | 0.42254* | 0.27209 | 0.24549 |
| # of grocery stores | 0.05455 | 0.21360 | 0.25072*** | 0.14718 | 0.07509 | 0.09286 | 0.11101 |
| # of restaurants | 0.03833 | -0.02739 | 0.18223*** | 0.20648*** | 0.05702 | 0.18139*** | 0.27487*** |
| **Housing** | | | | | | | |
| % Homeowners | 0.00300*** | 0.00290 | -0.00235 | -0.00006 | 0.00109 | -0.00548*** | -0.01010*** |
| % Vacant Units | 0.00039 | 0.00592 | -0.00192 | 0.00297 | 0.01201** | 0.00691 | 0.00483 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.53246*** | 0.63530*** | 0.47569*** | 0.57484*** | 0.57043*** | 0.50185*** | 0.55950*** |
| % Young People | -0.00212 | -0.00673 | -0.00077 | 0.00213 | -0.00040 | -0.00478 | -0.00828 |
| Ethnic Heterogeneity | 0.00450*** | 0.00245 | 0.00072 | 0.00209 | 0.00242 | 0.00094 | 0.00262 |
| % Low-income | 0.00019 | -0.00302 | -0.00017 | -0.00199 | -0.00216 | -0.00426 | 0.00479 |

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Table .75 – *Continued from previous page*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.01435*** | 0.01826 | 0.02203*** | -0.00563 | 0.00840 | 0.00646 | 0.00675 |
| % Residential LU | 0.02564*** | 0.01851*** | 0.03032*** | 0.01491** | 0.03118*** | 0.02905*** | 0.02306* |
| % Retail LU | -0.03378** | -0.05869 | 0.03644 | 0.00672 | -0.03567 | 0.01835 | -0.00976 |
| % Office LU | 0.07741*** | 0.02420 | -0.00652 | 0.01136 | 0.04171 | 0.00775 | 0.01304 |
| % School LU | -0.03762** | -0.06257* | -0.01729 | -0.02980 | 0.00787 | -0.00500 | -0.03920 |
| # of bars | -0.00712** | -0.00410 | 0.00254 | 0.00178 | 0.00003 | 0.00078 | 0.01045 |
| # of grocery stores | 0.00234** | 0.00132 | -0.00079 | 0.00053 | -0.00243 | -0.00063 | -0.00050 |
| # of restaurants | 0.00006 | -0.00006 | -0.00056 | -0.00135** | -0.00013 | -0.00053 | -0.00030 |
| **Housing** | | | | | | | |
| % Homeowners | 0.00366 | -0.01866** | -0.00880 | -0.00293 | 0.00005 | -0.00838 | 0.00627 |
| % Vacant Units | 0.05253** | 0.04965 | 0.04909 | 0.00593 | 0.08664** | 0.02622 | -0.00141 |
| **Time Varying** | | | | | | | |
| Logged Population | -0.24103** | -0.45835* | -0.48055* | -0.09301 | -0.41502 | -0.70022** | -0.42433 |
| % Young People | 0.01678* | 0.05429** | 0.00658 | 0.02250 | 0.00028 | 0.00774 | 0.04223 |
| Ethnic Heterogeneity | 0.00631* | -0.00348 | -0.00446 | -0.00066 | -0.00346 | -0.00945* | -0.01398 |
| % Low-income | 0.02349*** | -0.00419 | -0.00164 | 0.00724 | 0.03987*** | 0.01372 | -0.00829 |
| Intercept | -12.33761*** | -7.65667** | -7.67284*** | -13.23710*** | -10.02297*** | -4.29410 | -8.66517 |

$*p < .05$; $**p < .01$; $***p < .001$

*Note:*

Table .76: Los Angeles: Spring Burglary

| | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00833*** | -0.00312 | 0.00758** | 0.00229 | 0.00336 | 0.00671* | 0.01285 |
| % Residential LU | 0.00040 | -0.00418 | -0.00655*** | -0.00747*** | -0.00914*** | -0.00629** | 0.00352 |
| % Retail LU | -0.00864*** | -0.00185 | 0.00751*** | 0.00490* | -0.00389 | 0.00798** | 0.02073*** |
| % Office LU | -0.00267 | -0.00386 | 0.00248 | -0.00237 | -0.00170 | 0.00848** | 0.01228* |
| % School LU | -0.01868*** | 0.01095*** | 0.00802** | 0.00178 | 0.00722* | 0.01352*** | 0.02079** |
| # of bars | 0.06548 | -0.16559 | -0.12991 | 0.07161 | -0.44265 | -0.48395* | -0.07908 |
| # of grocery stores | 0.07720 | -0.05167 | 0.22391** | 0.14055 | 0.07855 | 0.08531 | 0.15192 |
| # of restaurants | 0.02521 | 0.09810* | 0.17828*** | 0.27317*** | 0.11287** | 0.19475*** | 0.17455*** |
| **Housing** | | | | | | | |
| % Homeowners | 0.00306*** | 0.00250 | -0.00116 | -0.00272 | 0.00147 | -0.00409** | -0.00271 |
| % Vacant Units | 0.00173 | 0.00830 | 0.00669 | -0.00014 | 0.01226** | 0.00997* | 0.00497 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.58649*** | 0.66678*** | 0.49344*** | 0.48141*** | 0.53987*** | 0.46915*** | 0.56772*** |
| % Young People | 0.00205 | -0.00496 | 0.00041 | 0.00736* | -0.00128 | 0.00295 | -0.00912 |
| Ethnic Heterogeneity | 0.00530*** | 0.00465 | 0.00092 | 0.00398 | 0.00315 | -0.00412 | 0.00890* |
| % Low-income | -0.00132 | -0.00505* | 0.00088 | -0.00379 | 0.00329 | -0.00637** | -0.00283 |

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Table .76 – *Continued from previous page*

| | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.01926*** | 0.01403 | 0.01546* | 0.00138 | 0.02438*** | 0.02033** | -0.00164 |
| % Residential LU | 0.02331*** | 0.02435*** | 0.03363*** | 0.01572** | 0.02854*** | 0.04724*** | 0.02817** |
| % Retail LU | 0.00402 | -0.05258 | 0.03338 | 0.03732 | 0.00334 | -0.03745 | 0.06135 |
| % Office LU | 0.05641*** | 0.06160* | 0.00640 | 0.00142 | 0.02423 | 0.08277*** | -0.00347 |
| % School LU | -0.07303*** | -0.07021* | -0.03294 | -0.03059 | -0.06257** | -0.01339 | 0.00018 |
| # of bars | -0.00340 | 0.00306 | 0.00444 | 0.00841* | 0.00317 | 0.00990** | 0.00989 |
| # of grocery stores | 0.00294*** | 0.00224 | 0.00116 | 0.00087 | 0.00043 | 0.00362* | 0.00033 |
| # of restaurants | -0.00080** | -0.00074 | -0.00074* | -0.00151*** | -0.00131** | -0.00155** | -0.00107 |
| **Housing** | | | | | | | |
| % Homeowners | 0.01437*** | -0.00025 | -0.00602 | -0.00243 | 0.00991 | -0.01268* | -0.02669* |
| % Vacant Units | 0.09097*** | 0.08135* | 0.08806** | 0.03664 | 0.15064*** | -0.00217 | -0.01408 |
| **Time Varying** | | | | | | | |
| Logged Population | -0.08482 | -0.39624 | -0.74968*** | -0.18860 | 0.00518 | -1.15245*** | -1.19125** |
| % Young People | -0.00132 | 0.02644 | 0.00385 | 0.00091 | -0.00054 | 0.03343** | 0.01919 |
| Ethnic Heterogeneity | 0.01434*** | 0.00734 | -0.00333 | -0.00322 | -0.00140 | -0.00203 | -0.01476* |
| % Low-income | 0.03694*** | 0.02710** | 0.00402 | 0.00952 | 0.01899* | 0.02186* | 0.02283 |
| Intercept | -15.22190*** | -11.07266*** | -5.38792** | -11.12456*** | -15.25570*** | -0.93125 | -0.84052 |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: LU = Land Use. Table is unstandardized coefficients.*

Table .77: Los Angeles: Summer Burglary

| | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|
| | 7am-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | |
| % Industrial LU | -0.00665*** | 0.00647** | 0.00631* | 0.00319 | 0.00467 | 0.00667 |
| % Residential LU | 0.00329** | -0.00654*** | -0.00381* | -0.00402* | -0.00863*** | 0.00051 |
| % Retail LU | -0.00435** | 0.00854*** | 0.00888*** | 0.00027 | 0.00118 | 0.01253* |
| % Office LU | -0.00223 | -0.00034 | 0.00199 | 0.00425 | 0.00315 | 0.00962 |
| % School LU | -0.01124*** | 0.00522 | 0.00690* | 0.00805* | 0.01370*** | 0.01689** |
| # of bars | 0.04136 | 0.21319 | -0.00823 | -0.03859 | 0.02907 | 0.36568 |
| # of grocery stores | 0.10548* | 0.21806*** | 0.11840 | 0.21440* | 0.15974 | 0.13059 |
| # of restaurants | -0.02579 | 0.16507*** | 0.20346*** | 0.10936** | 0.16068*** | 0.10955* |
| **Housing** | | | | | | |
| % Homeowners | 0.00287*** | 0.00035 | -0.00417** | -0.00162 | -0.00407** | -0.00076 |
| % Vacant Units | 0.00509* | 0.00610 | 0.00945* | 0.00849 | 0.00707 | -0.00411 |
| **Time Varying** | | | | | | |
| Logged Population | 0.58485*** | 0.51107*** | 0.43574*** | 0.55795*** | 0.49662*** | 0.49338*** |
| % Young People | -0.00305* | 0.00225 | -0.00142 | -0.01034* | -0.00374 | 0.00284 |
| Ethnic Heterogeneity | 0.00489*** | 0.00312 | 0.00550** | 0.00742*** | 0.00094 | 0.00947* |
| % Low-income | -0.00194* | 0.00142 | -0.00324 | 0.00129 | 0.00028 | 0.00743 |

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Table .77 – *Continued from previous page*

| | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|
| | 7am-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | |
| **Land Use and Business** | | | | | | |
| % Industrial LU | 0.01920*** | 0.02513*** | 0.02581*** | 0.02297** | 0.02359*** | 0.00888 |
| % Residential LU | 0.02535*** | 0.02742*** | 0.03260*** | 0.03966*** | 0.03028*** | 0.02090* |
| % Retail LU | -0.02391* | -0.01328 | 0.03108 | -0.03366 | 0.01015 | 0.06009 |
| % Office LU | 0.06134*** | 0.00568 | 0.02046 | 0.04106 | 0.02890 | -0.02334 |
| % School LU | -0.04160*** | 0.02812 | -0.02007 | -0.00394 | -0.02982 | 0.00266 |
| # of bars | -0.00250 | 0.00070 | 0.00945** | -0.00563 | -0.00086 | -0.00160 |
| # of grocery stores | 0.00345*** | 0.00149 | -0.00294* | 0.00063 | 0.00077 | -0.00573* |
| # of restaurants | -0.00059* | -0.00045 | -0.00089* | -0.00025 | -0.00040 | -0.00026 |
| **Housing** | | | | | | |
| % Homeowners | 0.00565* | -0.00850 | -0.00220 | -0.00414 | -0.00135 | -0.01472 |
| % Vacant Units | 0.06235*** | 0.05357* | 0.05523 | 0.07738* | 0.04575 | 0.06190 |
| **Time Varying** | | | | | | |
| Logged Population | -0.21288* | -0.70602*** | -0.69395*** | -0.78035*** | -0.65928** | -0.55887 |
| % Young People | 0.00911 | -0.00959 | 0.01494 | 0.01094 | 0.03042* | 0.00552 |
| Ethnic Heterogeneity | 0.00571* | -0.00256 | -0.00120 | -0.00025 | -0.00985** | -0.01593* |
| % Low-income | 0.02322*** | 0.01041 | 0.03398*** | 0.03565*** | 0.01189 | 0.01427 |
| Intercept | -12.87996*** | -5.39149** | -7.31047** | -6.74581** | -5.98551* | -7.58113 |

$*p < .05$; $**p < .01$; $***p < .001$

*Note: LU = Land Use. Table is unstandardized coefficients.*

Table .78: Los Angeles: Fall Burglary

| | 21 | 22 | 23 | 24 | 25 | 26 | 27 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | -0.00623** | -0.00355 | 0.00481* | 0.00305 | 0.00562 | 0.01220*** | 0.00469 |
| % Residential LU | 0.00244* | -0.00785*** | -0.00856*** | -0.00448* | -0.00764*** | -0.00319 | -0.00891* |
| % Retail LU | -0.00525** | -0.00410 | 0.00281 | 0.00744** | -0.00357 | 0.01025*** | 0.00542 |
| % Office LU | -0.00319 | -0.00656 | 0.00111 | 0.00180 | -0.00084 | 0.00546 | 0.00325 |
| % School LU | -0.01730*** | 0.00217 | 0.00139 | 0.00336 | 0.00043 | 0.02009*** | 0.00592 |
| # of bars | 0.04863 | 0.09417 | 0.14583 | 0.00867 | 0.15176 | -0.22638 | 0.15117 |
| # of grocery stores | 0.08690 | 0.13923 | 0.18111** | 0.06421 | 0.06315 | 0.06572 | 0.01939 |
| # of restaurants | -0.01139 | 0.07025 | 0.16079*** | 0.19634*** | 0.09408** | 0.16695*** | 0.21231*** |
| **Housing** | | | | | | | |
| % Homeowners | 0.00298*** | 0.00705*** | -0.00281* | -0.00179 | 0.00078 | -0.00295 | -0.00383 |
| % Vacant Units | 0.00311 | 0.00079 | 0.00703 | 0.01024* | 0.01011* | 0.00374 | 0.01085 |
| **Time Varying** | | | | | | | |
| Logged Population | 0.56855*** | 0.65752*** | 0.45627*** | 0.53491*** | 0.60786*** | 0.52802*** | 0.48393*** |
| % Young People | -0.00262 | -0.00413 | -0.00034 | 0.00817* | -0.00068 | -0.00407 | 0.01149 |
| Ethnic Heterogeneity | 0.00405*** | 0.00086 | 0.00270 | 0.00305 | 0.00490* | 0.00526* | -0.00074 |
| % Low-income | -0.00168* | 0.00197 | -0.00168 | -0.00273 | -0.00022 | 0.00090 | -0.00051 |

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Table .78 – *Continued from previous page*

| | 21 | 22 | 23 | 24 | 25 | 26 | 27 |
|---|---|---|---|---|---|---|---|
| | 7am-3pm:M-F | 3pm-5pm:M-F | 5pm-11pm:SU-TH | 11pm-7am:SU-F | 7am-5pm:SA-SU | 5pm-1am:F-SU | 1am-7am:SA-SU |
| **Spatial Lags** | | | | | | | |
| **Land Use and Business** | | | | | | | |
| % Industrial LU | 0.02274*** | 0.01631 | 0.01812** | 0.01373* | 0.00596 | 0.00509 | 0.02270 |
| % Residential LU | 0.02818*** | 0.02335*** | 0.03639*** | 0.03322*** | 0.02592*** | 0.03167*** | 0.03589** |
| % Retail LU | -0.05515*** | -0.04601 | 0.01999 | -0.01290 | -0.06620** | 0.00027 | 0.04699 |
| % Office LU | 0.06806*** | 0.07259** | 0.01385 | 0.02599 | 0.05590** | 0.04533* | 0.03400 |
| % School LU | -0.05229*** | -0.03815 | -0.00850 | -0.03036 | -0.03798 | -0.03688 | 0.04775 |
| # of bars | -0.00412 | 0.00112 | -0.00896** | 0.00739* | -0.00242 | -0.00163 | 0.00407 |
| # of grocery stores | 0.00337*** | 0.00319 | -0.00139 | -0.00110 | -0.00033 | 0.00143 | -0.00276 |
| # of restaurants | -0.00048 | -0.00192** | 0.00024 | -0.00040 | -0.00072 | -0.00057 | -0.00055 |
| **Housing** | | | | | | | |
| % Homeowners | 0.00729* | -0.01017 | -0.01081* | 0.00143 | -0.00016 | -0.01439* | -0.01439 |
| % Vacant Units | 0.08708*** | 0.12423** | 0.03850 | 0.00496 | 0.08630** | 0.01427 | -0.06224 |
| **Time Varying** | | | | | | | |
| Logged Population | -0.14498 | -0.21519 | -0.81504*** | -0.71982*** | 0.01441 | -0.84680*** | -0.65368 |
| % Young People | 0.00552 | 0.04478** | -0.00020 | 0.02343* | -0.00824 | 0.02245 | 0.01684 |
| Ethnic Heterogeneity | 0.01077*** | -0.00221 | -0.00888** | -0.00258 | -0.00728 | -0.01270** | -0.00908 |
| % Low-income | 0.02577*** | -0.00093 | 0.02102** | 0.03964*** | 0.02614** | 0.00892 | 0.01534 |
| Intercept | -13.76789*** | -11.87651*** | -3.71479 | -7.66342** | -14.02684*** | -3.44801 | -6.58867 |

$*p < .05; **p < .01; ***p < .001$

*Note: LU = Land Use. Table is unstandardized coefficients.*

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