ABSTRACT

KAWAGUCHI, RIKU. Putting Alcohol Outlets in Place: Time and Covariates in the Relationship Between Alcohol Outlets and Violent Crime. (Under the direction of Dr. William R. Smith).

This study examines the unique effects of alcohol outlets on street robbery in a Southeastern city in the United States from 2010 to 2011. Although previous studies generally support the criminogenic effects of alcohol outlets, the implications of their findings are limited because they have not adequately addressed three theoretical and methodological issues. Using routine activity theory and environmental criminology, the current study demonstrates the need to consider the three issues related to different types of alcohol outlets, time of day, and various covariates of alcohol outlets such as other property uses near the alcohol outlets to more truly understand the relationship between alcohol outlets and crime. Using the census block groups as the unit of analysis (N=232), a series of spatially lagged heterogeneous negative binomial regression models are estimated, controlling for social disorganization and other factors. Results support the hypotheses of criminogenic effects of five types of alcohol outlets. Some alcohol outlets also show time-varying effects on street robbery; i.e., some alcohol outlets are associated with street robbery committed at some times of day but not others. In addition, multicollinearity diagnostics reveal the land use covariates of alcohol outlets. The results show that bars and restaurants are highly correlated, and they also covary with other land use variables (such as retail stores), leading to severe multicollinearity issues. This supports the need to consider covariates of these alcohol outlets in order to better assess their possible criminogenic effects.

Putting Alcohol Outlets in Place: Time and Covariates in the Relationship Between Alcohol Outlets and Violent Crime

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DEDICATION

To my late grandfather, Yuuichi Kawaguchi. I never got to thank you before you passed, but I would not be here if it were not for you. Thank you for always encouraging me, always pushing me, and always believing in me.

BIOGRAPHY

Riku Kawaguchi was born on October 19, 1990 in Amakusa, Japan. Raised in Tokyo, Japan, he came to the United States in 2010 to attend college upon graduating from high school in Japan. He earned Bachelor of Arts degree in Sociology of Law, Criminology, and Deviance (*summa cum laude*) with a minor in Political Science from the University of Minnesota Twin Cities in May 2014. Since the fall of 2014, he has been a sociology graduate student at North Carolina State University. His current research interests include: criminology, deviance and social control, community and urban sociology, family and life-course, LGBTQ community, and quantitative methods.

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INTRODUCTION

Do alcohol outlets matter in explaining crime? This is an important question that requires an answer for theoretical, empirical, and practical reasons. Although many theoretical perspectives, as well as common sense, suggest a link between alcohol and crime, how the two are actually associated is not obvious, especially when aggregate or social ecological units of analysis are used. At the individual level, it is often thought that alcohol reduces inhibitions, leading an individual to commit a crime that they would otherwise have the self-control to resist. That is, alcohol helps manifest the temptation for aggressive behaviors and self-gain at the expense of others (Parker and McCaffree 2013; Parker and Rubhun 1995). The more access one has to alcohol, the more likely one is to drink and to have inhibitions reduced. It would seem to follow that the more available alcohol is in an area, the more drinking would occur, and thereby more crime. Additionally, it is sometimes argued that drinking alcohol reduces ability to resist an assault as alcohol (in excess) weakens one's ability to ward off attackers or to flee. For these basic reasons, we would expect there to be a positive relationship between the availability of alcohol and crime, especially a crime such as robbery. Specifically, street robbers may need alcohol to help "steel" themselves before attempting the crime, and robbers may view slightly intoxicated individuals as "easy marks" to attack because these potential victims are not as capable of defending themselves (Katz 1988; Wright and Decker 1997). However, despite the fact that studies support the empirical association of alcohol outlets and crime, the presence of a causal connection between them does not have consistent support in the literature that is based on ecological units of analysis, such as census tracts, or larger geographic areas. For example, some

researchers have even claimed that alcohol is not to be blamed for crime in an area (Block and Block 1995) because alcohol is incidental to people's presence in busy nightlife areas. Essentially, they argue that the people would be present anyway in those areas and thus at risk of victimization.

Criminological interests in the effect of alcohol trace back to a landmark study by Wolfgang (1958) which found the link between alcohol and homicide (e.g., he found that alcohol was involved in about 64% of all homicide cases). Since then, a number of studies have examined the effects of alcohol. However, many of such studies focus on individual-level explanations. For example, many studies have shown how alcohol consumption lowers inhibitions, resulting in more aggressive behavior or increasing the risk of victimization on average, and sometimes more crime (Clements and Schumacher 2010; Felson and Burchfield 2004; Parker and Auerhahn 1999; Sayette, Wilison, and Elias 1993). At the aggregate level, many studies have examined the presumed presence of alcohol and crime, but with mixed results. Some studies suggest a causal role played by alcohol distribution (Roncek and Maier 1991; White, Gainey, and Triplett 2015; Zhu et al. 2004), but some do not (Block and Block 1995; Nielsen et al. 2010). Others approach the connection between alcohol and crime by focusing on place management (Graham and Homel 2012; Homel et al. 1997; Macintyre and Homel 1997) as key to limiting aggression associated with bars and pubs. Despite the recent criminological interests in the effects of places (e.g., Bernasco and Block 2011; Brantingham and Brantingham 1995; Haberman and Ratcliff 2015; Kubrin and Hipp 2014; Roncek 1981; Roncek and Maier 1991), it is argued that ecological studies on alcohol outlets still fall short in demonstrating a clear link with crime. Although there are empirical findings to

demonstrate that alcohol outlets are associated with crime (e.g., Pridemore and Grubesic 2013; White, Gainey, and Triplett 2015), these studies often do not help us to test social ecological theories of when and where crime occurs (Roman et al. 2009). Also, these studies raise methodological issues, which will be addressed below, before we can better understand the unique effects of alcohol outlets.

The current study advances the literature on alcohol outlets and crime by addressing limitations of previous social ecological studies, and by offering a more detailed analysis of correlates of alcohol outlets as well as of time-of-day variations in a common type of serious crime, street robbery. Using routine activity theory (Cohen and Felson 1979), I argue for the need to consider different types of alcohol outlets, as well as including the time of day in modeling the counts of serious violence, such as street robbery. Also, more care need be exercised in examining the covariates of alcohol outlets, specifically other types of land parcel uses that are often found near alcohol outlets, and compete with them as a source for alternative hypotheses about why street robbery victims and perpetrators are present at the same time-of-day. A review of the relevant literature suggests that these issues have not been addressed adequately in previous studies. Such studies often lump together different types of alcohol outlets into one, or perhaps two categories (such as on-premise versus off-premise outlets). Because there is a reason to suspect that different types of alcohol outlets have qualitative differences (e.g., bars in a hotel versus other bars versus over-the-counter package goods sales) that lead to different relationships to crime, it is argued here that it is important to consider them in the research models.

At the theoretical level, despite the fact that a major ecological theory of crime—

routine activity theory—emphasizes the importance of people's routine activity and time, previous studies have not examined whether the effects of alcohol outlets on street robbery differ by time. This is a serious shortcoming because it makes intuitive sense that bars are more likely to be criminogenic when people are drinking in the evening and late at night than in the day time hours.

In addition to time of day, methodologically, the issues on handling the covariates have not been addressed adequately. Alcohol outlets are not isolated from other "land use," properties and buildings that serve different functions such as schools, businesses, and eating and other drinking establishments, that may also be criminogenic. Not considering such correlations between alcohol outlets and land uses is problematic because strongly correlated land uses may limit the ability to find statistically significant associations between alcohol distribution and violence. Thus, it becomes difficult to assign not only a causal connection between alcohol and crime, but also to determine what the empirical association is. By addressing the major limitations of previous studies, this paper offers ways to put alcohol outlets in their right place as criminogenic establishments.

WHY ALCOHOL MAY MATTER: ALCOHOL-VIOLENCE LINK AT THE INDIVIDUAL-LEVEL

As alluded to above, alcohol has long been an interest in the criminological literature. For example, in his classic study of homicide, Wolfgang (1958) analyzed 588 criminal homicide records in Philadelphia from 1948 to 1952. Based on these police reports, among many other findings, he found that about 64% of homicide cases involved offenders and/or

victims drinking alcohol, and about 44% of homicide cases involved alcohol in both offenders and victims (Wolfgang 1958:136). In addition, he found some racial disparities in alcohol presence—67% of black offenders and 58% of white offenders had consumed alcohol prior to committing homicide, and 70% of black and 49% of white victims were drunk. Based on these descriptive statistics and significant chi-square statistics, he concluded that there is a link between alcohol consumption and crime. Although Wolfgang was careful not to make a uni-causal claim since other factors than alcohol can cause crime, his finding clearly indicates that alcohol is one important factor in precipitating criminal offending and victimization.

Since Wolfgang's study, a number of scholarly works explored causal explanations and tested the effects of alcohol at the individual level. One explanation of the mechanism between alcohol and crime is that intoxication affects cognitive processing, which leads to aggressive responses to social stimuli and a number of behavioral problems such as driving while intoxicated (Clements and Schumacher 2010; Gustafson 1994; MacDonald et al. 1995; Sayette et al. 1993; Steele and Josephs 1990a, 1990b; Zeichner et al. 1982). A similar explanation is that intoxication leads to the disinhibition effects, which suggests that consuming alcohol reduces social and cultural constraints toward violence (Parker and Rubhun 1995; Pernanen 1991; Pihl, Lau and Assaad 1997; Room and Collins 1983). Several studies also found that alcohol consumption relates to victimization (Felson and Burchfield 2004; Harrison et al. 2001; Parker and Auerhahn 1999; Sampson and Lauritsen 1990). The risk of victimization may increase because intoxicated people may be more vulnerable, especially if they are incapacitated to some extent (Homel et al. 1992), and are thus perceived

as being less able to defend themselves, flee, or ward off attacks. Regardless of the mechanisms between drinking alcohol and a crime/victimization experience, alcohol consumption clearly relates to violence and crime at the individual level (Sumner and Parker 1995; see also Parker and Auerhahn 1999, 1998 for a review of the link between alcohol and crime). One might assume that if the relationship is strong at the individual level, it should also be prevalent in studies of alcohol and crime at the aggregate level. However, in that literature, the causal role of alcohol is not so obvious.

THE ROLE OF ALCOHOL OUTLETS ON VIOLENCE AND CRIME

While the individual level alcohol-violence link became well-established, a number of scholars began to examine the issue of how alcohol came to be in the hands of the victims as well as the perpetrators. They examined the effects of alcohol outlets on crime and violence using an ecological perspective. These ecological studies rest on the assumption that alcohol outlets serve as a proxy for availability and consumption of alcohol (Blose and Holder 1987), and that we can observe increased aggression and violence around alcohol outlets because those people who consume alcohol can become offenders or victims. Surprisingly, ecological studies on alcohol outlets and crime are relatively uncommon, perhaps owing to such studies being a relatively new endeavor among criminologists (Pridemore and Grubesic 2013). Thus, ecological explanations of the relationship between alcohol outlets and crime are underdeveloped and understudied (Pridemore and Grubesic 2013; Roman et al. 2009). Therefore, there is arguably a need for more studies. This section offers theoretical frameworks, summaries of previous empirical findings, and critiques of the

previous studies, along with offering ways to better inform our theoretical and empirical understanding of the effects of alcohol outlets on crime.

Routine Activity, Alcohol Outlets, and Crime

Neighborhood characteristics and local places are important predictors of violence and crime (e.g., Cohen and Felson 1979; Felson 2006; Felson and Eckert 2015; Shaw and McKay 1942; Sampson and Groves 1989; Sampson, Raudenbush, and Earls 1997). Two theories dominate such ecological explanations. Social disorganization theory emphasizes the importance of local social institutions as a locus of social control (Bursik and Grasmick 1993; Kornhauser 1978; Peterson, Krivo, and Harris 2003; Triplett, Gainey, and Sun 2003). Routine activity theory emphasizes the importance of how different institutions and places attract both victims (suitable targets) and perpetrators (motivated offenders) to enable crime occurrence (Cohen and Felson 1979). Using these two theories, previous studies demonstrate that different institutions and places affect whether crime will occur (e.g., Bernasco and Block 2011; Peterson et al. 2000).

Routine activity theory informs the role of alcohol outlets on crime. Routine activity theory posits that crimes occur when there is a convergence of motivated offenders, suitable targets, and a lack of guardianship in time and space (Cohen and Felson 1979; Felson and Eckert 2015). People's daily routines and movements are important components of the theory (Felson 2002). That is, their physical movements (e.g., when people go out, when they grocery shop, when they work, and so on) influence their risk of victimization. Such analysis naturally leads to consider the role of places that influence people's routine activity.

Another important component of routine activity is places that attract people or foster decreased level of social control (Cohen and Felson 1979). Building on routine activity, environmental criminology has identified characteristics of places that facilitate criminogenic opportunities (Brantingham and Brantingham 1993, 1995). Alcohol outlets are one of such criminogenic places (Brantingham and Brantingham 1982; LaGrange 1999; Roman 2005; Roncek and Bell 1981; Roncek and Meier 1991). Theoretically, some alcohol outlets such as bars can facilitate specific crime opportunities because of the presence and consumption of alcohol (Brantingham and Brantingham 1993, 1995). Some other alcohol outlets such as convenience stores and grocery stores attract a large number of people in general since their main function is to sell general goods, not just alcohol. Such places have high foot-traffic, which may lead to crimes that are incidental to such traffic, rather than being caused by a factor such as alcohol (Brantingham and Brantingham 1993, 1995).

Combining the ideas from routine activity theory and environmental criminology, I hypothesize that alcohol outlets are criminogenic because of their characteristics that facilitate the convergence of motivated offenders and suitable targets. These ideas produce the following theoretical propositions about the role of alcohol outlets. First, alcohol outlets produce suitable targets because intoxicated people are easy to attack as perceived by the potential offenders. Second, alcohol outlets attract potential offenders by supplying intoxicated, suitable targets. Third, alcohol outlets produce potential offenders through lowered inhibitions associated with alcohol consumption. Fourth, the convergence happens at a particular time of day because people's routine activity suggests that they are more likely to be at certain types of alcohol outlets at a certain time of day. In other words, these theories

suggest that it is important to consider both time and space when assessing the effects of alcohol outlets.

Supporting these theoretical frameworks, previous studies generally demonstrate that alcohol outlets are important predictors of crime. First, alcohol outlets in general are a robust predictor of violence and crime. Several previous studies that examined the effects of total alcohol outlets on neighborhood crime reported positive and statistically significant association (Britt et al. 2005; Nielsen and Martinez 2003; Pridemore and Grubesic 2013; Scribner, MacKinnon, and Dwyer 1995; White, Gainey, and Triplett 2015; Zhu et al. 2004). Second, both on- and off-premise outlets have positive impacts on violent crime (Pridemore and Grubesic 2013; White, Gainey, and Triplett 2015). Other studies report that bars and taverns specifically are predictive of high violent crime rates or incidents (Bernasco and Block 2011; Gorman et al. 2001; Hipp 2010; Lipton and Gruenewald 2002; Livingston 2008; Roncek and Maier 1991; Peterson et al. 2000; Roman and Reid 2012; Sherman et al. 1989), and that liquor stores have a positive association with homicide rates (Parker and Rebhum 1995).

Despite these overall consistent results that alcohol outlets matter, there are some discrepancies. For example, studies do not agree on whether on- and off-premise are equally important, or if just one or the other is important. One the one hand, some have found that only off-premise alcohol outlets are significant predictors of violent crime (Branas et al. 2009; Costanza, Bankston, and Shihadeh 2001; Gruenewald et al. 2006; Schribner et al. 1999). Off-premise outlets may have stronger effects on crime rates compared to on-premise outlets (Pridemore and Grubesic 2011). On the other hand, White, Gainy, and Tripplet (2015)

found that only on-premise outlets were significant predictors of violent crime when assessing the effects of on- and off-premise outlets simultaneously in their models.

In addition, at least one major study by Block and Block (1995) has claimed that alcohol outlets, and indeed alcohol consumption per se, are not criminogenic because people would be present to be victims or perpetrators whether or not alcohol was dispensed. People would be drawn to late night social locations whether or not alcohol was present. This is an extreme case of attributing causality to the covariates of alcohol outlets and none to alcohol itself.

Considering Time and Covariates: A Critique of Previous Research

These inconsistent results might stem from a lack of considering several issues: (1) there are different types of alcohol outlets beyond the simple on- and off-premise dichotomy; (2) place matters but most places influence—and are influenced by—people's daily routine activities, and thus time of day matters since most places are not frequented equally across all hours of day; and (3) in any geographic area larger than an individual street address (and indeed some single street addresses can be the site of multiple land uses, such as some shopping centers), there can be other land parcel uses that attract or generate crime around alcohol outlets, and these covariates of alcohol distribution sites need to be controlled for in a multivariate research strategy. In other words, previous studies often do not consider different types of alcohol outlets, time of day, or covariates of alcohol outlets. These three issues are theoretically and empirically important, as well as of practical importance for alcohol policy.

First, previous studies tend to combine different alcohol outlets, or only include one or a few other outlet types. While many previous studies examined the effects of on- and off-premise alcohol outlets (e.g., Pridemore and Grubesic 2013), some others only include off-premise (e.g., Alaniz, Cartmill, and Parker 1998). Other studies included only bars and taverns (e.g., Roncek and Maier 1991), or combined all types of alcohol outlets together into a single category (e.g., Gorman et al. 1998; Nielsen, Martinez, and Lee 2005). Combining all categories or even dichotomizing different types of alcohol outlets ignores important qualitative differences. In these previous studies, on-premise alcohol outlets generally consisted of bars and restaurants. Combining restaurants and bars ignores the qualitative differences in how people use these two places. From the routine activity perspective, a plausible assumption is that people go to bars and restaurants at different times of day and for different purposes. People are also more likely to consume more alcohol at bars compared to restaurants (Fitzgerald and Mulford 1993) because people generally go to restaurants to eat and bars to drink. Similarly, consuming food may also delay or buffer the impact of alcohol. Thus, people may be more intoxicated around bars and less intoxicated around restaurants. Additionally, whereas bars and taverns generally serve all types of alcohol, and the consumption occurs on the premises, restaurants often have limited selections of alcohol, which may influence the level of intoxication. Off-premise outlets generally consist of places that sell package alcohol such as liquor stores, convenience stores, and in some cases grocery stores. Again, combining these outlets into a single category ignores the qualitative differences and theoretical implications of how crimes happen. Generally, people go to liquor

stores to buy alcohol.[1] Thus, we can infer that the presence of alcohol may have something to do with the crime that happens around liquor stores either due to foot traffic or to drinking that may occur outside of these stores (depending on the extent to which there is foot-traffic to the store). Purchasing alcohol at other off-premise outlets such as convenience stores and grocery stores may be more coincidental,[2] as crimes that occur around these establishments are more likely to be driven by the high volume of foot-traffic rather than nearby alcohol consumption. By not distinguishing different types of alcohol outlets, researchers cannot assess the relative effect of different types of alcohol outlets on crime.

Second, time is crucial to consider because routine activity theory suggests that crime varies by hour of day (Felson 2002; Felson and Poulsen 2003). People's hourly activities are patterned and connected with other daily activities (Hawley 1950, 1986). In other words, how people behave (e.g., walking on a street) is connected with what they do at any given hour of day (e.g., going to a restaurant around noon for lunch). Some previous studies that do not test the effects of alcohol outlets report that time of day has effects on assaults and burglary (Rountree and Land 1996; Sampson and Wooldredge 1987). Thus, it seems logical to consider hourly activities, and how they connect to the timing of crime in relation to alcohol outlets.

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[1] There are two important things to note about liquor stores. First, the types of alcohol sold at liquor stores often differ by the state law. For example, in the state where the sample city for this study is located, liquors stores are only permitted to sell spirits, but not wine and beer. Second, some states or counties may have strict zoning and planning regulations that influence where liquor stores can be established. In some states, it is possible that liquor stores naturally have low criminal opportunities because of the locations and immediate environments of liquor stores.

[2] Because of different state laws or county regulations, these other types of off-premise type alcohol outlets such as convenience stores and liquor stores may sell different types of alcohol. In this study period, these off-premise type alcohol outlets in this state are allowed to sell wine and beer only—no "hard" liquor.

Time has an intuitive appeal for criminologists who consider the effects of alcohol outlets. For example, while bars may be open from 10 a.m. to 2 a.m., it is less likely that bars are equally criminogenic all hours of day. It is likely that bars are more criminogenic late at night such as between 11 p.m. and 2 a.m. when people are likely to consume alcohol and to be intoxicated (Arfken 1988), or when they leave bars at closing. As previously stated, alcohol may instigate violence by disinhibition, or may increase victimization because intoxicated people walking outside may not be aware of their surroundings due to reduced cognitive functions. They become suitable targets. It is also possible that other alcohol outlets such as liquor-selling convenience stores are criminogenic all hours of day (if they are open 24 hours) because it attracts people throughout the day. By definition, convenience stores are convenient for people to go and purchase items across a broad spectrum of time, but typically not all time slots because, presumably, people shop for alcohol more during some hours of the day than others, as well as more on some days of the week than others (and in the state of the city studied, no hard liquor sales occur in convenience stores, only beer and wine). Therefore, considering time is particularly important for alcohol outlets.

Unfortunately, previous studies on alcohol outlets and crime have rarely considered time of day. Almost all previous studies on alcohol outlets and crime simply used the sum of crime in a certain year span without considering time of day (e.g., Bernasco and Block 2011; Pridemore and Grubesic 2013; Roncek and Maier 1991; Sherman et al. 1989; White, Gainey, and Triplett 2015). In these studies, alcohol outlets are effectively being modeled as time invariant since time is not a variable. This is limiting. As I have pointed out above, different types of alcohol outlets are likely to have time-varying effects on crime by time of day.

Fortunately, there are some studies that measure crime by time, examining the effects of alcohol outlets by different time periods. For example, Roman and colleagues (2009) examined the effects of alcohol outlets by three different time periods: weekend, weeknight, and weekend night. They found that on-premise outlets are significant predictors of violence for weekends and weekend nights, but not weeknights, and that off-premise outlets are not significant in any of these time periods. In a recent study that examined different criminogenic places in general, Haberman and Ratcliffe (2015) found time differing effects of different criminogenic places. Dividing the time of day into four periods, they found that some places such as ATMs, corner stores, and fast food restaurants were associated with high street robbery counts across all time periods, other places such as cash-checking stores and drug treatment centers were associated with high street robberies under specific time periods.

A third major objective of the current study is to point out that previous studies paid scant attention to the covariates of alcohol outlets that may play an important role in generating crime. On-premise alcohol outlets such as bars tend to be established near other busy, criminogenic places such as restaurants and other commercial establishments that attract people (Block and Block 1995). Because of some common selectivity processes in locating alcohol and other consumer-related land uses, alcohol outlets, especially bars and restaurants covary with each other and with these other busy places. Thus, specifically, in a census block group, for example, there will often be multiple types of land uses located because of their value as commercial properties that draw people to their premises, while another census block group may be entirely residential, or have less of a mix of land uses. Empirically, in regression models, it is expected that high correlations between alcohol

outlets and different land use variables often make it difficult to assess the unique effects of alcohol outlets because of these correlation issues.

Previous scholars either ignore or minimize discussing covariates. The work of Block and Block (1995) is an exception. In this classic study of alcohol outlet and crime, they examined whether taverns and liquor stores, as well as convenience stores, predict crime and homicides in Chicago. They found that crimes tend to, but not necessarily, cluster around alcohol outlets. Instead of arguing that alcohol outlets are criminogenic, they argued that forces of selection are operating: alcohol outlets are located in areas that attract victims and offenders for other reasons. That is, they argued that crime concentrations are geographically determined by forces other than alcohol outlets. Alcohol outlets tend to be located near other busy places such as major streets, nightlife areas, and other commercial establishments. Their interpretation was that other contextual factors that *happen* to place alcohol outlets in certain areas matter more in predicting crime than alcohol outlets. Block and Block (1995:176) concluded that "it does not seem likely, therefore, that either density of liquor licenses, by itself, or density as an indicator of consumption, is strongly related to criminal activity." Their study cautions researchers by pointing out that covariates of alcohol outlets may be more important than the outlets themselves. However, to my knowledge, most previous studies have often ignored the analysis of covariates by not including other criminogenic places in their analysis or by minimizing the discussion of covariates so that we do not know what other land uses may be covariates of alcohol outlets.

Considering time can also help tease out the issue of covariates. For example, if retail stores (that do not sell alcohol) are not open around the time people are victimized, then it is

more likely that a covariate of retail stores is accounting for the street robbery in the area. To reiterate the theoretical framework, the routine activity theory emphasizes that people's routines and movements matter. Some establishments are criminogenic because they attract people when they are open. But if retail stores are not open between late night to early morning hours, it does not make sense to attribute causal effects of retail stores to crime in this time frame. The natural theoretical and logical extension is that it ought to be the bars that are attracting people who become victims or offenders late at night when there is nothing else open. It also ought to be the case that late at night or early morning, those people who are walking on streets are either going to bars or going to their cars from bars. Therefore, knowing the covariates of alcohol outlets can potentially help explain more the unique effects of alcohol outlets, in combination with time.

Social Disorganization and Crime

In addition to places, the criminological literature shows that social disorganization matters (e.g., Shaw and McKay 1942; Sampson and Groves 1998; Sampson, Raudenbush, and Earl 1997). Social disorganization theory posits that neighborhood structural conditions––such as residential mobility, racial/ethnic heterogeneity, and neighborhood socioeconomic status—influence neighborhood crime rates by affecting community ties (Bursik and Grasmick 1993; Kornhauser 1978; Sampson and Groves 1989; Shaw and McKay 1942). Thus, disadvantaged neighborhoods cannot form efficacious community ties to maintain effective social control, resulting in more frequent crime occurrence.

Ecological studies of crime often include both routine activity variables such as

criminogenic place (land use) indicators and social disorganization variables such as concentrated disadvantage. Studies have demonstrated the significant criminogenic effects of "busy place" land use variables, net of social disorganization variables (e.g., Bernasco and Block 2010; Wo 2014). Some scholars have also examined the interaction effects between busy place land use and social disorganization, finding that the criminogenic effects of some of these land uses vary by the level of social disorganization (e.g., Peterson, Krivo, and Harris 2000; Smith et al. 2000).

Because of the consistent finding that social disorganization is a covariate of crime, previous studies on alcohol outlets and crime have often taken into account social disorganization factors. These studies have found significant criminogenic effects of alcohol outlets, net of social disorganization variables (Pridemore Grubesic 2013; Roman et al. 2009; White, Gainy, and Tripplet 2015). Following these previous studies, I control for social disorganization variables. Specifically, I control for concentrated disadvantage, racial heterogeneity, residential instability, total population, and the distance from the city center. Although the first three variables are commonly used indicators of social disorganization, the distance from the city center is not. The rationale for including this measure is that the distance was one of the most salient findings of Shaw and McKay (1942) as an omnibus indicator of social disorganization. That is, neighborhood delinquency rates declined as the distance from the city center to neighborhoods increased, a finding based on several decades of data. I refer to it as an omnibus measure because the distance from the city center is correlated with many other variables, so it has a rather broad interpretation as representing virtually "all" things—or the many things that correlate with distance. In one study that

included this measure, Smith et al. (2000) found that further away from the city center, there were appreciably lower crime incidents. Thus, it is highly likely that the distance from the city center is an important crime predictor.

Street Robbery

In this paper, I focus on street robbery. Street robbery includes crime incidents that happen outdoors (on streets and other public and semipublic venues) where offenders target victims who are often pedestrians or strangers, and attempt to steal cash and other items by using force or threat of force (Monk, Heinonen, and Eck 2010). I focus on street robbery in part because it is a common and serious crime that instils fear in citizens (Smith and Torstensson 1997), but also for the following reasons. First, the characteristics of street robbery are compatible with the theoretical framework. Street robbers often target victims who are pedestrians in a public or semi-public space such as on a street, in an alley, or in a parking lot (Monk, Heinonen, and Eck 2010). Street robbers also often make calculated decisions in targeting a victim. They tend to target those who seem to carry money and other valuable items, who appear to be vulnerable, and who appear to be careless (Monk, Heinonen, and Eck 2010). In other words, street robbers often carefully choose victims to maximize their probability of success (Wright and Decker 1997). Thus, people's routine activities that place them on the street are important factors facilitating street robberies' occurrence. Another important point is that intoxicated people may be more likely to be targeted because they are often vulnerable and unaware of their surroundings. It is highly likely that intoxicated people are attacked while engaging in other routine activities such as

walking back from a restaurant or a bar to a car after drinking. In fact, in a rare qualitative study of active robbers, Wright and Decker (1997) documented that street robbers said that they are likely to target individuals who appear to be intoxicated. Second, previous studies on the effects of alcohol outlets have focused on assaults and robbery in general, but rarely examined their effects on street robbery. Thus, examining street robbery adds to the literature.

Street robbery also has advantages from a data standpoint. Although official police data have some known limitations, previous studies have shown that official police crime incident data closely match victimization (Bastian 1993; Blumstein, Cohen, and Rosenfeld 1991; Byrne and Sampson 1986; McDowall and Loftin 1992). Street robbery, in particular, is arguably less biased and better measured compared to other crimes. Smith et al. (2000) note that the biases resulting from unreported incidents are minimal because most street robberies are reported to the police. Thus, the mismatch between official data and victimization are small for street robbery. People are perhaps more likely to report street robbery because of street robbery's more brutal nature that often instigates a fear of crime among city residents (Conklin 1972; Wright and Decker 1997). Relatedly, because of the traumatizing nature of street robbery, people are more likely to report street robbery right away such that the time recorded by the police should be reasonably reliable.[3] In examining the effects of alcohol outlets, especially bars, it is important to examine the crimes that happen outside and near

[3] An alternative choice of relatively reliable crime measure is homicide. However, I do not use homicide because of the low total counts of homicide incidents (N<50) at the block group level within the city limit between 2010-2011, and because homicide does not necessarily happen outside.

these establishments.

DATA AND METHODS

Drawing on multiple data sources, I examine the relationship between alcohol outlets and street robbery at the census block group level in a mid-sized southeastern city in the United States. I use the census block group as the unit of analysis because it is reasonably small and thus may suffer less from issues of "spatial heterogeneity," i.e., variation within a geographic unit that disguises spatial patterns that could affect the interpretation of measured traits. For example, a census tract's north side might be 100% Hispanic, while its south side 100% African American, yet at the tract level, receives a score as a highly mixed race census tract of half black, half Hispanic. Smaller geographic units of analysis are less prone to spatial heterogeneity issues (Smith et al. 2000). Also, census block groups have readily available neighborhood information. In this section, I describe the research site, data, and analytic strategies to examine different types of alcohol outlets, time, and covariates. Because the dependent variable is the count of street robberies, and its distribution is highly skewed and overdispersed, I use heterogeneous negative binomial regression models with spatial lags to analyze the data (Hardin and Hilbe 2007; Hilbe 2011).

Research Site and Unit of Analysis

I chose a mid-sized southeastern city in the United States because data are available

and I am knowledgeable of the city.[4] This city is an average mid-size city in the United States. The 2010 decennial census and 2013 5-year data from the American Community Survey estimate the population of the city to be just over 400,000. The racial composition of the city was slightly more heterogeneous than the national average: 53.3% of the total population was non-Hispanic white, 29.3% African American, 11.4% Hispanic, and 4.3% Asian. About 14% of the total population was foreign born. Residents in the city were relatively well-educated with 90.0% of people over 25 years old with high school education, and 47.5% of people age over 25 holding Bachelor's degree or more. Thus the residents in the city were more educated compared to the national average. Median household income was $54,448, and 16.2% of residents were at or below the poverty level, which was similar to the national average.

The spatial unit of analysis is the census block group. The U.S. Census Bureau defines census block groups to contain between 600 and 3,000 people and are composed of a cluster of census blocks. I use the census block group as a proxy for neighborhoods because this is the smallest census unit that readily provides important contextual information such as the level of poverty and education. Some researchers have used larger units of analysis such as census tracts and ZIP code areas (e.g., Gruenewald et al. 2006; Peterson, Krivo, and Harris 2000; Wo 2014; Zhu et al. 2004). However, census tracts and ZIP code areas are arguably too large to measure meaningful demographic and ecological conditions of neighborhoods (Pridemore and Grubesic 2013; Smith et al. 2000; White, Gainey, and Triplett 2015).

[4] The same mid-sized southeastern city was used in the study by Smith et al. (2000).

Alternatively, smaller units of analysis would be census blocks, face blocks (both sides of a street between intersections), or street segments. However, census blocks have limited variable availability because of the confidentiality and other ethical concerns by the census bureau, and it is even more difficult to get information about street segments which are smaller than census blocks (Weisburd, Groff, and Yang 2012). In addition to data limitations of smaller units, census blocks and street segments are too small to readily capture broader neighborhood conditions (see Weisburd, Groff, and Yang 2012 for an opposing viewpoint).

Some scholars have criticized the use of officially defined boundaries such as census tracts and census block groups as "neighborhoods" because arbitrarily setting boundaries may not reflect what local residents think of as their "neighborhoods" (Furstenberg et al. 1999). Despite this critique, previous studies have used the census block group as a proxy for neighborhoods (e.g., Block and Block 1995; Gorman et al. 1998; Pridemore and Grubesic 2013; Roman et al. 2009; White, Gainey, and Triplett 2012).[5] Given the data availability and previous studies' successful use of this geographic unit, census block groups have been established as a valid unit of analysis approximating neighborhoods.

Data

Six sources were employed to measure crime, neighborhood conditions, alcohol outlets, and land uses. For crime data, the crime incident data for 2010-2011 provided by the city's police department was used. These data include geocoded incident data with addresses

[5] Although it is important to discuss what neighborhood exactly is, this is beyond the task of this research project.

and latitude and longitude (x-y coordinates) of street robbery incidents. Contextual information on neighborhood characteristics was gathered from 2010 U.S. Decennial Census and 5-year estimates from the 2006-2010 American Community Survey.[6] For alcohol outlets data, the liquor licensing data for 2010 was obtained from the county government's alcohol control board in which the city was located. This dataset provides addresses of alcohol outlets. Fifth, 2010 tax assessor data from the county government was used to obtain different land use variables. Tax assessor's data provides point data (x-y coordinates) of different establishments such as businesses, industrial establishments, and residential housings. Sixth, the ReferenceUSA's Historical Business data for 2010 was used to obtain additional information on alcohol outlets and land use variables. Similar to the tax assessor data, historical business data provides x-y coordinates of different business establishments. Since alcohol outlets data only contained addresses but not x-y coordinates, alcohol outlets were geocoded using geographic information system (QGIS) and its geocoding program.[7] Next, each point from these datasets was mapped and aggregated to the census block group level using QGIS. Other datasets already included x-y coordinates, and each point from these were also mapped and aggregated to the census block group level.

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[6] These census data and shape file for the city were downloaded from the National Historic Geographic Information System (Minnesota Population Center 2011).

[7] I primarily used QGIS because it allowed for batch coding using Google API geocoding program and for more flexible geocoding environment compared to ArcGIS. I also compared a small sample of QGIS geocoded addresses with ArcGIS geocoding. There were essentially no differences between using QGIS and ArcGIS for geocoding.

Dependent Variables

The dependent variables are the sum of street robbery and sums of street robbery incidents occurring during four distinct periods of the day (time stamps) which are described below. Table 1 summarizes the street robbery outcomes.[8] The first dependent variable is the total number of street robberies (henceforth referred to as "all time" street robbery) incidents reported to the city police between years 2010 and 2011. There were 836 street robberies reported to the police during this study period.[9]

Because previous research has rarely considered dividing crime incidents by time periods over the course of 24-hour day, there is no good guidance on how to determine the time stamp divisions. In order to divide street robberies by time, I partially used the logic of Felson and Poulsen (2003), who suggested how to summarize how crime varies by time of day. For example, they suggested that 5 a.m. should be the starting point because street robbery incidents tend to keep increasing afterword. Figure 1 also suggests that around 5 a.m. to 7 a.m. have the lowest street robbery incidents. Thus, I set 5 a.m. as the first cutting point for time stamps. In a recent study, Haberman and Ratcliffe (2015) used different "time divides" based on American Time Use Survey. They divided the time of day into 6:45 a.m. to 9:59 a.m., 10:00 a.m. to 4:29 p.m., 4:30 p.m. to 9:14 p.m., and 9:15 p.m. to 6:44 a.m. However, their time stamps do not reflect well the business hours of different establishments, particularly alcohol outlets, as well as the patterns of street robberies shown in Figure 1.

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[8] Note that when a variable's IQR is 0, it is adjusted to 1 in the table for the interpretation purpose. See note "a" in the table.

[9] These 836 street robberies include cases with valid geocoded addresses. Cases without valid geocodes were excluded from the analysis.

Additionally, larger time divides miss nuanced time-differing effects, especially at night.

For the purpose of this study, I divided street robbery into four different time stamps based on time of day (i.e., the crime occurrence includes a "time stamp" and the number of street robberies within a time range is counted to constitute each variable). I constructed these four time-stamp street robbery variables based on the visual inspection of street robbery incident counts by time (see Figure 1), and local knowledge of people's movements, of business hours and of when different alcohol outlets are open and occupied. I created four time stamps which include street robbery incidents that happened between 5:00 a.m. and 3:59 p.m. (daytime street robbery), 4:00 p.m.-8:59 p.m. (early evening street robbery), 9:00 p.m.-11:59 p.m. (night time street robbery), and 12:00-4:59 a.m. (late night street robbery). The daytime time stamp (5:00 a.m.-3:59 p.m.) reflects when people start their day: commuting to work or school, working in the office, studying at school, and staying home. Some people may go grocery shopping and engage in other daytime activities such as eating lunch at a restaurant, going to some retail stores, and spending time at a park with children. The early evening (4:00 p.m.-8:59 p.m.) time stamp reflects when people finish working or classes, going back home, going grocery shopping, or going out to eat dinner. Most retail stores are generally closed by the end of this time period. The night time (9:00 p.m.-11:59 p.m.) reflects the time when people have generally eaten dinner and start to move away from engaging in evening activities and, perhaps, move toward drinking at bars and or going to clubs. Around this time, people's outside movements are influenced by establishments that are open, which include mostly restaurants, bars, convenience stores, and some grocery stores. The late night time stamp (12:00-4:59 a.m.) reflects the time when most people are sleeping, but when

some people are likely to be leaving bars and clubs, possibly intoxicated.[10] Each time stamp contains about 200 street robbery incidents (see Table 3 for descriptive statistics).

Independent and Control Variables

Table 2 summarizes the operationalization and data source of each independent and control variable. Table 3 reports the descriptive statistics for all variables included in the analysis. To measure alcohol outlets, the list of establishments with alcohol licenses from the county's alcohol control board is used. The address of each alcohol establishment was geocoded. Alcohol outlets that were located outside the city boundary were dropped. I then coded alcohol establishments into different types. I coded for bars (including night clubs and social club),[11] restaurants,[12] convenience stores (with liquor licenses), grocery stores (with liquor licenses), and hotels and motels that sell or supply alcohol (henceforth hotel bars).[13] For liquor stores, I supplemented the data from ReferenceUSA Historical Business data 2010 because some of them were grouped together with wholesalers in the alcohol control board data, making it difficult to determine whether the establishments were strictly liquor stores

[10] The county's alcohol regulation states that all establishments with on-premise alcohol consumption license must not sell alcohol to their patrons after 2 a.m., and that alcohol must be cleared by 2:30 a.m.

[11] I initially coded bars/night clubs and social clubs (bar-type drinking places with membership requirements) separately. However, because the numbers of bars and social clubs were relatively small, and these two types of establishments had a high bivariate correlation (r=.73), I combined them into one measure, Bar.

[12] I initially coded restaurants serving alcohol (predominantly food and alcohol incidental) and restaurants with alcohol (predominantly alcohol and food incidental) separately. However, because these two types of restaurants were mostly clustered together and had a high bivariate correlation (r=.82), I combined them into one measure, Restaurant.

[13] Note that I also coded for breweries and wineries, and whole sale distributers. There were no breweries and wineries within the city limit in this study period. I excluded whole sale distributers because they are often located in private premises, making it difficult for street robberies to happen around these establishments.

only.

In addition to these six different types of alcohol outlets, the following three aggregate measures, which are often used in previous studies, were created. The total sum of alcohol outlets (total alcohol outlets) is a sum of the number of bars, restaurants, convenience stores, grocery stores, and hotel bars. The measure of on-premise alcohol outlets is a sum of bars and restaurants. The indicator for off-premise alcohol outlets is a total sum of convenience stores, grocery stores, and liquor stores.

For routine activity theory variables, several land use variables from tax assessor data are included. In general, previous studies measured criminogenic places using land use variables such as bars and restaurants (as a proxy for busy places/crime magnets) and the presence of residential buildings (as a proxy for residential areas). In this study, thirteen of these measures are included: mixed-residential housing, retail stores, office spaces, banks, parking decks, gas stations, car maintenance stores, hotels/motels, churches, and industrial establishments. All of these measures are the sum (count) of the number of such establishments in the census block group area. I do not include restaurants from the tax assessor data because many of these restaurants included in the tax files are also included in the alcohol control board data.[14] Thus, including both would mean redundant measurements. For the same reason, I also do not include supermarkets in the tax assessor data because of

[14] Also note that some restaurants in tax assessor's data do not have alcohol licenses. However, because of the high bivariate correlation between restaurants in tax assessor's data and restaurants in the alcohol outlets data, I decided not to include restaurants in the tax data. I also visually inspected the distribution of restaurants from these two datasets. The points generally overlapped, indicating that restaurants with and without alcohol outlets are established close to one another.

their overlaps with grocery stores in alcohol control board. I include hotels/motels in tax assessor data, in addition to hotel bars in alcohol data, because while the bivariate correlation was moderately high (r=0.59), the geographic coverage of hotels/motels was larger than hotel bars in the map.[15] For residential measures, I include single family housing units, dual unit housing units, and multi-family housing units.

I control for characteristics of social disorganization because previous studies have consistently found it as an important predictor of crime. Social disorganization variables include measures of racial composition, neighborhood disadvantage, residential instability, total population, and distance from the city center, drawn from the decennial census and the American Community Survey.[16] Racial composition is measured by Blau's racial heterogeneity index, which is one minus the sum of squared proportions of white, black, Hispanic, Asian, other race, and Native American.[17] The neighborhood disadvantage measure is a variation of the concentrated disadvantage index (Peterson et al. 2000; Sampson et al. 1997; Sampson et al. 2002), which is an average of a sum of standardized scores of percent families below the poverty level, percent single mothers with children, and percent unemployed among civilians aged 16 and over. Residential instability is measured by an

[15] The visual inspection of hotels/motels and hotel bars shows that the overlap is relatively small compared to restaurants in alcohol data and restaurants in the tax data, or grocery stores and supermarkets. Although hotel bars are nested within hotels/motels, there are more hotels/motels in the city compared to hotel bars.

[16] The American Community Survey, conducted by the United States Census Bureau, is an on-going yearly survey. Unlike the decennial census which is used as an estimate of population data, the American Community Survey is based on a smaller probability sample of people living in the United States.

[17] I also tested models with a four category variant of Blau's racial heterogeneity index, which included white, black, Hispanic, and Asian. The results were essentially the same.

average of z-scores of percent moved within past 5 years and percent rental housing. I also include the general measure of social disorganization found by Shaw and McKay (1942), which is the distance from the city center. This is measured by the distance from the centroid of a city center census block group[18] to a centroid of each block group (in kilometers).[19]

Spatial Autocorrelation

The initial mapping of all time street robbery incidents and alcohol outlets reveals strong geographic concentrations of street robberies and alcohol outlets in several areas (see Figure 2 for a close up of the city). Crime concentration by space is consistent with previous ecological studies of crime (Brantingham and Brantingham 1984; Skogan 1990). Figure 2 shows that most street robberies and alcohol outlets tend to cluster around downtown areas and other few specific areas across the city. The map also reveals that there are "hot spots" of both street robbery and alcohol outlets. In other words, hot spots of street robbery and alcohol outlet tend to overlap, which is consistent with previous studies (e.g., Roncek and Maier 1991; Sherman et al. 1989). The map also indicates that the majority of street robberies cluster around commercial or mixed land use areas rather than entirely residential areas. Because of the visual evidence, I focus on the commercial type land use variables rather than housing land use variables in the analysis below. I provide a short supplemental

[18] The city center approximates the mid-point of the downtown area.

[19] I created a centroid (midpoint) for each block group by using QGIS's standard function that can create centroids. I calculated the distance using QGIS's *hubline* function, which is a part of MMQGIS plugin. For the city center, I chose the centroid of the downtown city block group that included most of the downtown business area.

analysis for housing land use variables.

Figure 2 also reveals spatial dependency issues. Some of these crime and alcohol outlets hot spots occur across multiple block groups. For example, one hotspot in the Northeast side of the city occurs at the intersection of four block groups. Therefore, there is a need to take into account the spatial dependencies or “spillover” of street robbery.

In order to examine the extent of spatial dependencies, I calculated a common spatial autocorrelation measure, Moran’s I, for street robbery for each time stamp (Ward and Gleditsch 2008). I used GeoDa’s Queen's contiguity weights matrix to model the spatial proximity. Queen’s weights matrix takes into account neighboring block groups that share a border or a vertex. Moran’s I indicates a strong positive spatial autocorrelation for each street robbery time stamp (see Table 4). Given the significant Moran’s I, I produced spatial lag terms for each street robbery time stamp to take into account spatial dependencies, or “spillover,” of street robbery to neighboring block groups. The spatial lags average the street robbery incident counts of each neighboring block group.

Methods: Heterogeneous Negative Binomial Model with Spatial Lag

I use heterogeneous negative binomial regression (Hardin and Hilbe 2007; Hilbe 2011) to examine the effects of alcohol outlets on street robbery. Because the dependent variables in this study are count measures, Poisson regression is the first candidate for analysis (Hilbe 2011; Long 1997; Osgood 2000). However, the distributions of the outcome variables in this study do not meet the requirement of the equidispersion in Poisson

regression because they have variances larger than the means (indicating overdispersion).[20] When dealing with the overdispersed count data, negative binomial regression is often more appropriate (Hilbe 2011; Osgood 2000). I visually inspected the diagnostic graphs to confirm that negative binomial regression models fit the data better than Poisson regression models. The likelihood ratio tests also confirmed that negative binomial regression models provide better fits than Poisson regression models.

Among negative binomial models, I choose heterogeneous negative binomial models (henceforth NB-H; see Hilbe 2011). The advantage of NB-H over regular negative binomial modeling (refers to as NB2 models in Hilbe 2011) is that it allows one to parameterize an ancillary, or overdispersion, parameter, alpha (henceforth lnAlpha). NB-H modeling allows lnAlpha to vary as a linear combination of covariates (henceforth overdispersion parameters), whereas regular negative binomial regression estimates one constant lnAlpha. In other words, NB-H makes it possible to model lnAlpha as a function of variables specified as overdispersion parameters. Thus, the advantage of NB-H models is that it allows one to determine which variables included as overdispersion parameters influence the overdispersion. It can also differentiate variables that influence the model parameter estimates versus overdispersion. That is, some variables may affect both the dispersion and the outcome, while other variables might only affect one or the other.

Because social disorganization variables are generally robust indicators of crime across many previous studies and because studies support that higher level of social

[20] Equidispersion means that the mean equals the variance. In practice, this requirement is rarely met in social science count data (Hilbe 2011).

disorganization tends to result in higher crime (Hannon 2005; Krivo and Peterson 1996; Wilson 1987), they may influence the overdispersion. Thus, I include some of the measures of social disorganization variables as the overdispersion parameters in the equation. Specifically, I include the concentrated poverty index, Blau's heterogeneity index, the distance from the city center, and total population. Residential instability index is not included because the criminological literature suggests that it is not as important as concentrated poverty or racial heterogeneity. Note that, in addition to being included as an overdispersion parameter, concentrated poverty and Blau's heterogeneity are included in the main model parameter in order to control for these variables. The total population variable and the distance to the city center are only included in the overdispersion parameter part of the equation, but not included in the main model parameter estimates. Total population is not included in the main parameter estimates because the statistically significant effects were very small when included as the main model parameter,[21] consistent with Smith et al. (2000) who suggested dropping total population from the main parameter estimates for street robbery. The distance from city center is only included in the overdispersion parameter because it is an omnibus indicator of social disorganization, of which substantive meaning is difficult to assess if included as a main parameter.

In order to estimate NB-H models, I used Stata's *gnbreg* command with *lnalpha* option (Hardin and Hilbe 2007; Hilbe 2011). In order to address the issue of spatial dependency which I identified earlier, I include a spatial lag term for street robbery in each

[21] Models that include total population and models without total population differ little in terms of other variables' coefficients and standard errors.

model (see a section, *Spatial Autocorrelation*).

In crime count data analysis using Poisson or negative binomial regression models, researchers often "rate parameterize" models by adding the natural logarithm of total population on the right hand side of the equation in order to take into account exposure risks (e.g., Bernasco and Block 2011; Osgood and Chambers 2000; see also Osgood 2000). However, I do not use this rate parameterization because the underlying assumption does not match with my theoretical framework. Rate parameterization assumes that crime victims are residents, as captured by total population. However, street robbery victims and offenders are often those who travel across different block groups or those who happen to be on the street, not necessarily the residents. Many people travel across block groups to go to alcohol outlets such as bars and restaurants, given that many alcohol outlets, particularly bars, are not located in residential areas. Therefore, rate parameterizing models may produce biased results. Nonetheless, it is important to consider both the residents and the transient population for exposure risk (Andresen 2006). I assume that housing variables (single family unit, dual family unit, and family unit) capture residents in the main parameter estimates.[22] Residents are also partially captured by the overdispersion parameter, total population. The transient population, likely to be either victims or offenders, is captured by alcohol outlets and other busy place land use variables because people's movements are a function of these places (Bernasco and Block 2011).

[22] I recognize that there are some vacant housing units. However, people still live near these vacant units. Therefore, I assume that these housing variables capture residents and their daily routine movements. If these residential housing units were significant, it is because these residents were around their home, as opposed to walking around bars and other busy places away from home.

In order to identify covariates of alcohol outlets, I rely on bivariate correlation matrix and multicollinearity diagnostics. The correlation matrix provides the initial inspections of potential alcohol outlets covariates. Moderate to high correlations between each alcohol outlet and each land use variable highlight potential issues including covariates in the same model. I expect that covariates with high bivariate correlations lead to multicollinearity issues in NB-H models. More specifically, I expect the land use covariates of alcohol outlets with high correlations obscure the effects of alcohol outlets and land use variables.

Multicollinearity diagnostics allow one to examine which variables contribute to obscuring the unique effects of alcohol outlets. For multicollinearity diagnostics, I used Stata's *collin* command to produce tolerance estimates and inverse variance inflation factors (VIFs). By adding and excluding different land use variables, I focus on changes in tolerance statistics and VIFs to identify covariates of alcohol outlets. Models estimating all time street robbery accompany the results of multicollinearity diagnostics to show the changes in coefficients and standard errors that occur across models.

RESULTS

The results are reported in the following order. First, I discuss the bivariate correlation matrix to describe the nature of the data and potential covariate issues among alcohol outlets and other land use variables. Second, I discuss models with different types of alcohol outlets and social disorganization variables, as well as time stamps. Third, I report the results from models that consider covariate/multicollinearity issues between alcohol outlets and land use variables. In regression tables, I report unstandardized and standardized

coefficients. Unstandardized coefficients are the log of expected counts (denoted as “b” in tables). Standardized coefficients are interquartile range (IQR) base standardized coefficients (henceforth IQR effect coefficients). Standardizing coefficients by IQR (unstandardized coefficient multiplied by IQR) is particularly useful for predictors with skewed distributions because IQR is more stable than the standard deviation (Fox 1997:106-108; Quillian 1995). IQR effect coefficients are used to compare the relative effect size of coefficients within each model.

Bivariate Analysis

Table 5 shows the bivariate correlation matrix of all variables included in the analysis except spatial lag terms for each street robbery time stamp. The correlation matrix reveals the importance of time stamps and potential covariance issues involving alcohol outlets. Here, I simply summarize the correlations and potential issues. Later in the multivariate analysis on covariates, I discuss in more detail the implications of each covariate. I start with a discussion of the bivariate correlations between street robbery time stamps and each alcohol outlet, followed by a discussion of bivariate correlations among alcohol outlets. I then discuss the bivariate correlations between alcohol outlets and other land use variables.

First, looking across time stamps in Table 4, the correlations between each street robbery time stamp and different types of alcohol outlets (column 1 through 5 and row 6 through 14) show some time-varying changes in the correlations. The correlations for bars are statistically significant across time stamps; however, they get progressively smaller, from daytime street robbery through late night street robbery (.54, .42, .41, .38 respectively). This

pattern does not follow the theoretically expected relationship between bars and street robbery; that is, bars should predict street robberies at night more than in the day time. However, the larger bivariate correlations for morning to daytime stamps between bars and street robberies may be driven by the fact that bars have criminogenic land use covariates that are more criminogenic at morning to day time compared to night time. I elaborate more on this point in multivariate analyses. Restaurants also show this pattern of progressively smaller correlations across time stamps, which makes sense given that restaurants are more frequented during lunch time and dinner time. The variable convenience store is significant throughout all time stamps and has the smallest correlation for early evening. Grocery stores are significant for daytime, evening, and late night, but not early night. Grocery stores have the smallest correlation for late night time stamp. Hotel bars are only significant for daytime and early evening. Additionally, other land use variables also show small changes across street robbery time stamps. For example, retail stores show a similar pattern of progressively small correlations like bars and restaurants, which is compatible with the routine activity time prediction because most retail stores are not open at night. Similarly, other land use variables tend to follow the routine activity time predictions. The land use variable for offices has higher correlations during daytime and evening compared to night time and late night. The measure of banks is only significant for daytime street robbery. The gas station variable is only significant for the evening and late night street robbery. These time-varying patterns of bivariate correlations suggest that time stamps are worthy of further exploration.

Next, correlations among different alcohol outlets show that most of them are related from low to modest levels (between around .1 and .4). However, bars and restaurants are

highly and significantly correlated at .79. This is not surprising since bars and restaurants tend to be near one another in urban and commercial areas (see Figure 1), and many restaurants also have bars. The high correlation indicates that entering bars and restaurants simultaneously in the models may result in a multicollinearity issue whereby we would not be able to separate out the effects of the two separate variables in the same equation due to their high intercorrelation.

Third, alcohol outlets and some land use variables have high and significant correlations. Bars and mixed residential units are highly and significantly correlated at .73, bars and retail at .79, and bars and parking decks at .75. Churches and bars also have moderately high correlation of .51. Similarly, restaurants and mixed residential, retail, parking decks, and churches have the same patterns. Other types of alcohol outlets and other land use variables have low to moderate correlations. Convenience stores and car maintenance businesses have a moderately high correlation of .50, convenience stores and mixed residential with a moderate correlation at .34, and convenience stores and industrial at .33. Grocery stores have moderate correlations with retail (.34) and banks (.36). Hotel bars do not seem to have moderate or high correlations with most of other land use, except the land use measure for hotels and motels (.59). Therefore, bars and restaurants have clear covariates that potentially cause multicollinearity issues in regression models. Hotel bars and hotels/motels may also cause multicollinearity issues in regression models because the visual inspection based on mapping indicates that all hotel bars should be located in some of hotels/motels locations, which may mean that these two are redundant measures. However, hotels/motels with bars and without bars may have qualitative differences since the bivariate

correlations indicate that while hotels/motels are significantly related to street robbery for all time stamps, the hotel bar variable is not.

These bivariate correlations are consistent with the theoretical assumption that alcohol outlets, especially bars and restaurants, have covariates with varying degrees of correlation, some quite high. As the bivariate correlations show, the alcohol outlets have time-varying significance and different correlation sizes across street robbery time stamps. However, bars and restaurants, at first glance, do not seem to have the time-varying effects as predicted by the theoretical framework proposed in this study. At the same time, the bivariate correlation matrix reveals that bars and restaurants are highly correlated with other land use variables that tend to generate higher levels of foot-traffic during the day than at night. It is suggested here that covariates of bars are explaining the high correlation between daytime street robberies and bars rather than the bar variable itself, while night time street robberies may be driven by bars rather than other land use variables as the reverse argument also seems defensible: business establishments that are closed during late night/early morning hours would not be expected to be generating people traffic, so they would not be a likely "cause" of street robbery. Examining more systematically these covariates and alcohol outlets using multivariate models might help explain why bars and restaurants have consistent significance across all time stamps. Note that none of the housing related variables (single family units, dual family units, and multifamily units) appear to have any covariates with high correlations. Because these housing land use variables do not seem to have covariate issues, and to simplify the argument, I exclude these from the main analysis of covariates of alcohol outlets. Instead, I include a supplemental analysis later in the result section. Below, I start

with discussing time of day and alcohol outlets, followed by a discussion of covariate issues.

Multivariate Analysis: Alcohol Outlets, Time, and Social Disorganization

I begin by reporting the result of assessing the unique effects of alcohol outlets on street robbery, net of social disorganization variables. Because social disorganization is such a robust and often strong predictor of crime, it is hypothesized that alcohol outlets will show significant effects in the models on street robbery, as will social disorganization variables.

First, following several previous studies, I assess the effects of all alcohol outlets, on-premise outlets, and off-premise outlets (e.g., Britt et al. 2005; Pridemore and Grubesic 2013; White, Gainey, and Triplett 2015; Zhu et al. 2004). Table 6 reports the results of four NB-H models predicting all-time street robbery using total alcohol outlets, on-premise alcohol outlets, and off-premise alcohol outlets.[23] The first model shows that total alcohol outlets are significantly and positively associated with all-time street robbery, net of social disorganization variables and the spatial lag term. Similarly, on-premise and off-premise outlets are significantly related to all time street robbery, net of social disorganization and spatial lags. These results suggest support for the idea that alcohol outlets are criminogenic. Moreover, the magnitude of the effects in the model with both on- and off-premise variables suggests that off-premise is more strongly related to street robbery than on-premise (by almost a factor of four). This is somewhat surprising in that there are no "package goods"

[23] Note that only distance to the city center in the overdispersion parameters is statistically significant in the off-premise model. Using regular negative binomial regression (NB2) models and including overdispersion parameter variables as regular parameters do not alter the substantive results.

stores in the state that sell hard alcohol, as all such liquor sales are handled monopolistically through state-run stores, which are located across only a few sites in the city. These results show that sale of beer and wine for off-premise consumption is associated with street robbery.

As expected, social disorganization variables are also positively associated with street robbery in all four models in Table 6. The positive and statistically significant spatial lag for street robbery confirms the importance of capturing spatial dependency in modeling alcohol outlets and crime. These results are consistent with other researchers' findings, showing that the effects of alcohol outlets are robust even controlling for social disorganization and spatial lag. Additionally, as pointed out above, when entering both on-premise and off-premise outlets in the model simultaneously, both outlet types are significantly and positively associated with all-time street robbery. This result differs from previous studies which found that only on-premise outlets were significant but not off-premise (White, Gainey, and Triplett 2015), or only off-premise outlets were significant but not on-premise (Baranas et al. 2009).

The findings from my analysis thus far are informative and limiting at the same time. These results add empirical evidence to support that alcohol outlets, both on- and off-premise outlets are criminogenic. However, as previously argued, aggregating all type of alcohol outlets or on- and off-premise dichotomy ignores potential qualitative differences among different types of alcohol outlets, which leads to previously argued empirical and theoretical issues. Empirically, combining these outlets might have resulted in inflating the criminogenic effects. Theoretically, routine activity suggests that each type of alcohol outlets attracts motivated offenders and suitable targets differently and at different time of day. Therefore, I

disaggregate alcohol outlets into various types and consider time of day in the subsequent analyses.

Table 7 and 8 report the results of "alcohol outlets and social disorganization only" models, which predict time stamped street robbery variables by different types of alcohol outlets controlling for social disorganization variables, but not non-alcohol related land uses. This strategy is chosen to show the reader the effects of alcohol-related land uses while controlling for the predominant social ecological theory's variables (that of social disorganization theory). Because of the high correlation between bars and restaurants (r=0.79), I model them separately (using a separate set of models including only one of the two at a time). Doing so enables us to see what difference it makes to use one of the highly correlated variables compared to the other. Thus, Table 7 reports the effects of alcohol outlets without restaurants but with bars and other alcohol outlets, and Table 8 without bars but with restaurants and other alcohol outlets. Note that I omit the liquor store variable (i.e., state commission operated liquor stores) from these models to improve slightly the efficiency of the estimation of coefficients of other variables because liquor stores are never significant in any of the analyses, indicating that liquor stores are not a predictor of street robbery in the southeastern city. Omitting liquor stores from the models does not alter other coefficients, nor has any influence on the multicollinearity issue.

I refer to the model that includes the alcohol distribution parcels and the social disorganization variables (along with variables predicting the overdispersion) as the "base social disorganization model." The base social disorganization model for all time street robberies with the bars and other alcohol outlets (but not restaurants) reveals that all alcohol

outlets are related to elevated levels of street robbery with different effect sizes (see Table 7). Bars and grocery stores are statistically significant (two-tailed test), and convenience stores and hotel bars are also statistically significant (one-tailed test), net of social disorganization and spatial lag.

As predicted, all of the social disorganization variables and spatial lag are statistically significant and have positive impacts on street robberies. IQR standardized coefficients reveal that the spatial lag has the largest effect among all predictors, indicating a substantial "spill over" of street robberies. Social disorganization variables have larger effect sizes compared to alcohol outlets, with concentrated poverty having the largest effects. Compared to social disorganization and spatial lag, alcohol outlets have smaller effects on street robberies. Thus, although alcohol outlets are significant predictors, measures of social disorganization seem to have stronger predictors of street robberies. This may be because street robberies do not happen exclusively around alcohol outlets, but also happens around other areas with high foot-traffic or reduced level of social control.

Incorporating time of day in the models, these models show the time differing effects of alcohol outlets, net of social disorganization and spatial lag (see Table 7). While bars are significant and positive across all time stamps, other alcohol outlets are not. The size of unstandardized coefficients of bars vary little across different time stamps, which on the surface does not support the predicted time-differing effects. However, I argue below that since bars are correlated with other land uses, it is plausible that the daytime street robberies, and perhaps even early evening street robberies, are driven by other criminogenic land uses that are correlated with bars. Also, it seems plausible that the non-alcohol land uses are

unlikely to be attracting people during night and late night because non-alcohol land uses tend to be closed after 9 p.m. (or closed even earlier). Therefore, during night and late at night, street robberies in the areas that share both alcohol and non-alcohol land uses are likely driven by alcohol distribution sites rather than the latter.

As for other alcohol-related variables, the convenience store variable is only a significant predictor of street robbery during daytime and late night. When significant, IQR effect coefficients reveal that convenience stores have substantial effects on street robberies compared to other alcohol outlets. During the late night hours, the relative effect size of the convenience store variable (.215) is even close to the concentrated disadvantage index (.240). It is possible that, while convenience stores have increased informal social control that discourages street robbers to attack victims during early evening and night time because of higher foot-traffic. However, convenience stores may have lower protection because of less foot-traffic during daytime hours and because of the darkness that may provide suitable environments for offenders late at night. Grocery stores and hotel bars are only significant during early evening hours, with grocery stores and hotel bars having substantial effects on street robberies (IQR effect for grocery store .259, for hotel bars .242). It makes sense that grocery stores are only significant during the early evening hours because these are the times when people tend to grocery shop, potentially encouraging the convergence of suitable targets and motivated offenders. The hotel bars being only significant for early evening hours may also be explained by the fact that these hours are when people check-in to hotels and most likely be using hotel bars to socialize with others or to unwind from trips. These results support the routine activity prediction that different alcohol outlets attract people and crime

at different times of the day. In addition, spatial lag is time-invariant (to the extent that it is the only variable that is statistically significant across all time stamps) and has relatively large effects across all time stamps compared to most other variables, indicating a substantial lag effect throughout the day. Thus, substantively, street robberies occurring nearby (adjacent block groups) spill over into the block group studied.

In addition to alcohol outlets, social disorganization variables also have time differing effects. In general, with each passing hour, the risk of street robbery increases as a function of concentrated disadvantage, with effects tapering off after midnight. While concentrated disadvantage is a significant predictor of street robbery throughout the day, the significance of Blau's heterogeneity index and residential instability change by time stamps. Unstandardized coefficients also reveal that the effect sizes change across time when these are significant. For example, the effect of concentrated poverty is larger for night time (.45) compared to late night (.24). Looking at IQR effect coefficients, each social disorganization variable, when significant, has a larger effect size compared to alcohol outlets. In sum, social disorganization variables seem to have time-varying effects and their effects tend to be larger than alcohol outlets.[24]

These time differing social disorganization effects and the relative effect size differences between social disorganization and alcohol outlets warrant some theoretical explorations. Because there seems to be no theoretical framework that explains these two

[24] Similarly, overdispersion parameters which include three social disorganization variables show time-differing significance. The distance to the city center significantly influences the overdispersion during daytime and late night. Total population significantly predict overdispersion during early evening and late night. Concentrated disadvantage index is statistically significant during the daytime hours. Blau's heterogeneity is only significant for night time hours.

points, particularly the time differing effects of social disorganization variables, I offer some speculations. First, the findings that social disorganization factors have larger effects on street robberies compared to alcohol outlets are not surprising considering that previous studies repeatedly demonstrated that neighborhood disadvantage is a robust indicator of crime (Land, McCall, and Cohen 1990). It is possible that many crime actions tend to happen in the poor neighborhoods compared to other areas including commercial areas with alcohol outlets, especially during early evening and night hours. As Wright and Decker (1997) documented, armed robbers tend to attack other criminals such as drug dealers, who tend to operate in disadvantaged neighborhoods, because they tend to live in the same poor neighborhoods, providing easy targets with a lot of cash without having to travel a long distance. When robbers attack ordinary non-criminal citizens, it tends to happen in commercial areas but the proportion of street robberies that happen at commercial areas might be smaller compared to poor areas because of travel distance and perceived risk of arrest. Second, relatively large social disorganization effects may also be driven by one of the classic social disorganization measures, "young people hanging out on the street corners" (Sampson and Groves 1988). It is possible that more young people are hanging out outdoors in the poor neighborhoods compared to middle-class neighborhoods (or commercial areas). Such differences may happen particularly during early evening and night hours because it is possible that young people from poor households have less family social control and do not participate in any organized activities, while middle-class youths may have more family controls and engage in organized activities during these hours. Third, the tapering off of effect sizes of social disorganization after midnight might just mean that relatively few

people are awake and hang around in the neighborhoods after midnight, even in poor neighborhoods. These time-varying effects of social disorganization and relative effect size differences between social disorganization and alcohol outlets warrant further theoretical and empirical explorations in the future studies.

Table 8 reports the base social disorganization models for street robbery by time stamps for restaurants while excluding bars. These models include restaurants and all other alcohol outlets except bars. (Again, this separate set of models is done due to the collinearity between bars and restaurants to show how the results vary.) Once again, the results show time-differing effects of alcohol outlets. While restaurants are significant across all time stamps, other outlets show time differing effects. Convenience stores are significant at daytime and late night, but not during early evening and night time. Grocery stores are significant only during the evening hours. Hotel bars are never significant. Similar to the bar only models in Table 7, social disorganization variables also have time-differing effects.[25] The potential explanations of why restaurants have consistently significant effects are the same as for bars: the effects may be magnified because these social disorganization only models do not consider the land use covariates of alcohol outlets (the non-alcohol related land uses are to be analyzed below). It is also possible that because of high bivariate correlations between bars and restaurants (r=.79), these two are essentially redundant

[25] Similarly, overdispersion parameters which include three social disorganization variables show time-differing significance. The overdispersion parameters here replicates the results from Table 7. In Table8, the distance to the city center significantly influences the overdispersion during daytime and late night, and marginally significant during the night time. Total population significantly predicts overdispersion during early evening and late night. Concentrated disadvantage index is statistically significant during daytime hours. Blau's heterogeneity is only significant for night time hours.

measures in statistical models.

Multivariate Analysis: Covariates of Alcohol Outlets

Table 9 shows the results of adding and analyzing land use covariates of alcohol outlets in the models. The table is divided into two parts. The upper portion of the table shows the model parameters for alcohol outlets and land use variables. This base model is the same as the all-time street robbery model in Table 7. Although not shown in the table, these models include the social disorganization variables, spatial lag, and overdispersion parameter predictors. The model portion of the table shows unstandardized coefficients and standard errors in parentheses. The lower portion of the table shows the results of collinearity diagnostics with tolerance statistics and VIFs in parentheses. Although not shown in the table, each collinearity diagnostic includes social disorganization variables and a spatial lag. Social disorganization variables and the spatial lag term did not have problematic tolerance statistics nor VIFs greater than 4, indicating that these variables do not pose any multicollinearity issues (see Appendix A for the collinearity diagnostics that include social disorganization variables).

Table 9 demonstrates the need to consider land use covariates of alcohol outlets, particularly covariates of bars. The following discussion focuses on changes in tolerance statistics and VIFs to show that there are substantially high correlations among alcohol-related and non-alcohol related land uses. In the base model of Table 9, bars and grocery stores are statistically significant (two-tailed test), and convenience stores and hotel bars are also statistically significant (one-tailed test). The collinearity diagnostics show the absence of

a multicollinearity issue. Model 1 adds all other land use variables. The collinearity diagnostics reveal that entering land use variables creates multicollinearity issues for alcohol outlets. If we ignored those diagnostics, we might note, not surprisingly, adding these land use variables makes bars and convenience stores statistically insignificant. Compared to the base model, the tolerance statistic for bars is dramatically reduced from .835 to .234. Thus, the degree of independence of the bar variable is greatly diminished because of the inclusion of the other land use variables, as only 23% of the variance is now unique to the bar variable. The tolerance statistic for hotel bars also decreased dramatically from .940 to .519. The tolerance statistics for other alcohol outlets also decreased by about .1 to .2. These are not surprising decreases since the bivariate correlation matrix shows high correlations between alcohol outlets and some of these land use variables (see Table 5 and the section on *Bivariate Analysis*). These results indicate that the presence of high correlations and multicollinearity issues make it difficult to assess the unique effects of alcohol outlets. Therefore, there is a need to consider and identify a range of models with and without these land-use covariates of alcohol outlets to determine how the results vary so that meaningful interpretations can be drawn.

Models 2 through 4 progressively remove some land use variables. Figure 3 summarizes the potential covariates of alcohol outlets according to these models. Model 2 removes some land use variables. Based on the bivariate correlation matrix and an analysis of entering land use variables one at a time (see Appendix B), I identified four land use variables that are likely to be covariates of bars and which obscure their effects. These four covariates are mixed residential buildings, retail stores, parking decks, and churches.

Removing these four land use variables, the standard error of the bar variable becomes small, making the coefficient statistically significant beyond the significance level of .001. According to the collinearity diagnostics, removing these four land use variables eliminated the collinearity issue for bars (i.e., the VIF fell below 4). Comparing the collinearity diagnostics across model 1 and 2, the tolerance statistic for bars increase from .234 to .681, which is closer to base model bar tolerance statistic of .835. These changes in the standard error and the tolerance statistic suggest that mixed residential, retail, parking decks, and churches are problematic covariates of bars that obscure its unique effects on street robbery. Mixed residential apartments are generally established in commercial areas; thus it is not surprising that they are a covariate of bars. Retail stores and parking decks are predominantly established in commercial areas near bars. The link between churches, bars, and street robbery seems perplexing. However, this might be due to the fact that the southeastern city used in this study has many churches that tend to cluster around the downtown area and other commercial areas where bars are located. Additionally, these churches have their own parking lots that are frequently used by people who are visiting commercial establishments such as retail stores and bars. Also, note that churches have moderate bivariate correlations with parking decks (see Table 4, variable 27), which is another moderately strong correlate of all-time robbery with a correlation of .49 (column 1, row 29).

Model 3 and 4 remove additional land use variables to see if some other alcohol-related land uses become statistically significant in the face of less “competition” from the remaining non-alcohol related land uses. The models presented stem from trying many different trimmed models (see also Appendix B). Model 3 removes car maintenance and

hotels/motels land use variables, which makes convenience stores significant and increases the tolerance statistic for convenience stores. This result is not surprising given that convenience stores and car maintenance facilities have a moderate correlation in the bivariate correlation matrix. Although hotel bars did not become significant, removing hotels/motels increased the tolerance statistics of hotel bars from .537 to .843, which is not surprising given that hotel bars are nested within hotels/motels locations.

Model 4 removes the gas station variable. Doing so makes grocery stores and hotel bars statistically significant (one-tailed test). This indicates that the gas station count variable may suppress the unique effect of convenience stores on street robbery (also many gas stations have convenience stores). Gas stations and hotels/motels jointly may suppress the unique effect of hotel bars. These two results are reasonable since convenience stores tend to cluster around gas stations or are part of the same business establishment, and some hotels/motels and thus hotel bars also tend to cluster in the same block groups where gas stations are.

Note that some of the theoretically criminogenic land use variables are not statistically significant. For example, retail stores, a theoretically criminogenic establishment, are not statistically significant in Model 1. This is most likely due to multicollinearity issues. A common solution to these multicollinearity issues is to combine them into a single index, such as “busy place” index (Miethe and McDowell 1993; Rountree et al., 1994). However, this is not appropriate in some cases. For example, creating an index may overlook the qualitative differences of different land use variables. Also, an index obfuscates the fact that some of these different land use variables have different open hours. In sum, it is not always

wise to aggregate different land use variables to create an index. In the next section below, I propose theoretically-informed models that consider both time and covariates to sort out some issues raised above.

In addition to these land use variables discussed so far, I also include housing land use to test the robustness of the result from Model 4 in Table 9 here as a supplemental analysis (see Table 10). As discussed above (see also the street robbery map in Figure 1), street robbery seems to be not as common in residential areas as commercial areas. Additionally, housing land use variables do not appear to have any covariate issues like other commercial land use variables discussed above. Thus, I provide models including housing land use variables as a supplemental analysis. Adding single family unit, dual family unit, and multi-family unit land use variables do not alter the substantive findings of model 4 in Table 9. Adding these three variables does not have a significant influence on tolerance statistics or VIFs. In fact, it seems to improve the standard errors for the hotel bar variable. Also note that although not reported in Table 10, the VIFs for social disorganization variables were below 4, indicating that these variables do not pose any multicollinearity issues. Model 1 in Table 10 adds dual family units. Doing so improves the standard error for hotel bars, and change the hotel bar variable from significant at 0.05 level to significant at 0.01 level (in one-tailed test). The significance of other alcohol-related variables remains the same. Model 2 adds multi-family units in addition to dual family units. Doing so does not alter the results from Model 1. In Model 3, I add single-family units. Adding the single-family unit variable results in a slight decrease in the coefficient and standard error for convenience stores, which reduces the significance of the convenience store variable from

significant at 0.01 to significant at 0.05 level (in one-tailed test). Adding the single-family units also decreases the coefficient for grocery stores, changing the grocery store variable from statistically significant (in one-tailed test) to non-significant. Thus, other than the grocery store variable, adding housing-related land use variables does not alter the substantive findings for other alcohol outlet variables.

Reduced Models: Simultaneously Considering Time and Covariates

To reiterate the findings above, the analyses show that some alcohol outlets seem to have time-varying effects, and that covariates of alcohol outlets often obscure the unique effects of alcohol outlets, particularly bars. In this section, I propose theoretically driven modeling strategies that incorporate both times of day and covariates of alcohol outlets.

Table 11 shows the reduced models. Daytime street robbery and early evening street robbery models are predicted by (1) convenience stores, grocery stores, and hotel bars for alcohol outlets, (2) concentrated disadvantage, Blau's heterogeneity, and residential instability for social disorganization, (3) a busy place index[26] which is a sum of the numbers of selected alcohol outlets and commercial land uses (bars, restaurants with liquor licenses,[27] mixed residential units, retail stores, churches, car maintenance establishments, gas stations, and parking deck), (4) other land uses including offices, banks, and industrial establishments, and (5) housing land uses including dual family units, multi-family units, and single family

[26] This busy place index ranges from 0 to 293 with a mean of 11.7. The IQR is 11.

[27] Note that restaurants without liquor licenses are not included.

units. The notable variable is the busy place index, which combines bars, restaurants, and their covariates. Doing so eliminates the multicollinearity and covariate issues for these two time stamps. For these two time stamps, it is reasonable to combine these variables into one variable, "busy place," for two reasons. First, all of these establishments are expected to be open during the daytime hours and early evening hours because morning to around 4 p.m. are regular business hours, and many businesses including retail stores are also likely to be open between 5 p.m. to 9 p.m. Second, as the analysis of covariates above shows, these variables have strong and large correlations, reducing the chances of finding unique effects. The expectation is that the "busy place" index captures foot traffic that facilitates the convergence of victims and offenders. Therefore, this busy place index assumes that street robberies are due to foot traffic, not alcohol uses.

In the daytime model and early evening model, the busy place index is statistically significant, indicating a positive influence on street robberies during these two time stamps, supporting the theoretical claim that foot-traffic to these "busy" places may encourage the convergence between suitable victims and motivated offenders.

In the night time model, I include the on-premise alcohol outlet variable that combines both bars and restaurants given that they are highly correlated.[28] I use the on-premise variable instead of the busy place index because many other commercial establishments and covariates of bars and restaurants (i.e., the commercial portion of the mixed residential units, retail stores, churches, car maintenance establishments, gas stations,

[28] On-premise variable ranges from 0 to 68, with a mean of 1.99. The IQR is 2.

and parking deck) are mostly closed or (relatively) unused after 9 p.m. Therefore, it does not make sense to include them in the model as controls, since the presence of potential victims or perpetrators is unlikely to be caused by closed establishments. Similarly, I also dropped offices, banks, and industrial establishments from the models, as they are also likely to be closed. The on-premise variable is statistically significant, suggesting that restaurants and bars drive street robbery counts in block groups during night time hours.

Finally, in the late night model, I include the bar variable instead of on-premise alcohol outlets (dropping the restaurant variable from the model) because people are more likely to frequent bars around these hours compared to restaurants, and because restaurants are generally not open after midnight. It is predominantly bars that are open until 2 a.m., and street robbery incidents that happen around these hours may be attributed to the presence of bars or alcohol use; that is, motivated offenders target intoxicated and vulnerable people. In addition, convenience stores and hotel bars are also shown to be criminogenic during late night hours. This may be because of intoxicated people (who are coming home from bars) may stop by convenience stores that are less guarded because of low foot-traffic and relatively dark surroundings (allowing offenders to be unnoticeable or free easily). As for hotel bars, it is possible that intoxicated travelers who are coming back from bars to hotels are suitable targets in the eyes of offenders.

Similar to the findings from Tables 7 and 8, the models in Table 11 show that other alcohol outlets have time-varying effects. Convenience stores are only significant during the daytime hours and during the late night hours, replicating the results from Table 7. Hotel bars are only statistically significant during the early evening hours, and additionally, during the

late night hours. It is possible that, during late night hours, intoxicated travelers who are coming back from bars to hotels are suitable targets in the eyes of offenders. Grocery stores are only significant during the early evening hours. The IQR effect coefficients show that these alcohol outlets have relatively large effects on street robberies. Models in Table 11 also show time-varying effects of social disorganization variables. Furthermore, the models show that the spatial lag variable is time-invariant (to the extent that it is statistically significant in all time stamps), indicating a substantial lag effect of street robbery across all time stamps.

DISCUSSION AND CONCLUSION

This study addresses three major theoretical and empirical issues that are not well-addressed in the previous studies on the association between alcohol outlets on crime. The three issues relate to different types of alcohol outlets, time of day, and covariates of alcohol outlets. First, not considering different types of alcohol outlets ignores potential qualitative differences and theoretical explanation to why they may attract crime. Second, lack of considering time of day does not reflect the important element of the routine activity theory, and may also underestimate the effects of alcohol outlets on crime. Third, not carefully considering the covariates of alcohol outlets may result in an omitted variable bias, multicollinearity issues, or an extreme interpretation that alcohol outlets are not really predictors of crime. Therefore, while previous research supports the idea that alcohol outlets are criminogenic, these three issues hinder an assessment of the unique effects of alcohol outlets on crime and undermine the causal claims. Overall, the results of this study confirm that these three issues need be addressed in order to advance our empirical understanding

about the role alcohol outlets plays in affecting street crime.

The results confirm the criminogenic effects of different types of alcohol outlets. I started with analyzing whether the number of alcohol outlets, on-premise outlets, and off-premise outlets has criminogenic effects. The results from spatially-lagged heterogeneous negative binomial (NB-H) models controlling for social disorganization effects confirm that these aggregated measures of alcohol outlets are criminogenic, a substantive conclusion consistent with previous studies (e.g., Pridemore and Grubesic 2013; White, Gainey, and Triplett 2015). However, as I have argued, these aggregate measures ignore important qualitative differences of these alcohol outlets. In order to assess the effects of different types of alcohol outlets, I divided alcohol outlets into bars, restaurants, convenience stores, grocery stores, hotel bars, and liquor stores. The results show that different alcohol outlets have different effect sizes when significant (based on IQR effect coefficients). One limitation is that bars and restaurants could not be in the same model because of high correlation that leads to a multicollinearity issue. When the bar variable is included, bars, convenience stores, and hotel bars show statistically significant positive association with street robbery. When the restaurant variable is included, restaurants and convenience stores are positively associated with street robbery. Liquor stores are not statistically significant in either models (thus dropped from the analysis to improve the efficiency of estimates, and doing so does not alter the results).

I have also argued that considering time of day is important because different alcohol outlets would attract street robberies at different times of day. In order to assess this, I divided street robberies into four different time periods (daytime, 5 a.m.–3:59 p.m.; early

evening, 4 p.m.–8:59 p.m.; night time, 9 p.m.–11:59 p.m.; and late night, 12 a.m.–4:59 a.m.). The results confirm the idea that different alcohol outlets have different effects on street robbery at different times of day. Convenience stores are significant during the day time and late night, but not during early evening or night time hours. Grocery stores are significant only during the early evening hours in predicting street robbery. Hotel bars are significant during the early evening hours and late night hours. These results support the idea that the time of day effect is important to consider in assessing the associations between some alcohol outlets and crime. Bars and restaurants had statistically significant effects on street robbery throughout all four time periods. At first glance, this appears to disprove the theoretical assumptions that they should also have time differing effects. For example, because people tend to drink more at night, bars should predict street robberies at night and late night hours compared to day and early evening hours. However, not revealing time differing effects might be due to the fact that bars and restaurants covary with other land uses that are also known to be criminogenic such as retail stores because such establishments facilitate the convergence of potential offenders and suitable victims, which may undermine the causal effects of alcohol outlets on crime.

In order to address this issue, collinearity diagnostics on models that include alcohol outlet variables, different land uses, and other covariates were examined. The results reveal that retail stores, mixed residential buildings, parking decks, and churches are particularly problematic covariates of bars (and restaurants) that obscure the effects of bars (and restaurants). The results also indicate that car maintenance, hotel/motel, and gas stations are problematic land use covariates of other alcohol outlets that diminish the statistical

significance because of correlation issues. These analyses of covariates suggest that regression models uncritically used cannot distinguish the unique effects of each establishment because of strong correlations among them. However, combining these results with time of day within the routine activity and ecological framework, we can better understand how alcohol outlets and other non-alcohol land uses may influence street robbery, and explain why bars and restaurants would have effects at all time periods when, according to the predictions from the routine activity theory, they should not.

As argued above, the routine activity theory and environmental criminology posit that different places attract crime because they facilitate the convergence of potential offenders and suitable targets in both time and space. Because people's routine activities influence when and where convergence occurs, it is likely that these places would attract or produce crime at different times of day. In particular, I argue that the time when these establishments are open for business matters in predicting crime. For example, it is well-known that people are more likely to drink at night. Thus, we would expect bars to be criminogenic at night compared to during the day (because of the consumption of alcohol and foot-traffic). Similarly, retail stores are criminogenic because such stores attract people (who would typically carry cash or other materials that may make them the suitable targets). However, retail stores can attract people only when they are open. Typically, retail stores in the city of this study close between 7 p.m. or 9 p.m. Therefore, it does not make logical sense to attribute the criminogenic effects night time and late night street robbery on retail stores. As such, it is reasonable that it is difficult to distinguish the unique criminogenic effects of bars versus retail stores as well as other alcohol-related and non-alcohol-related land uses because

of their high intercorrelations. However, given that most other land uses such as retail stores are not open at night, it is plausible to attribute the causes of street robberies to establishments that are open, primarily bars and restaurants during the night time (9 p.m. – 11:59 p.m.) and bars at late night hours (12 a.m. – 4:59 a.m.). During the night and late night hours, it is likely that street robberies in commercial areas occur because some people are going to or leaving from bars (or restaurants). In Table 11, I have proposed theoretically driven models that take into account both time of day and covariate issues.

Limitations

The results and discussion in this study need to be situated within the context of some limitations. First, this study uses the framework that alcohol outlets influence street robbery because of their unique features that facilitate crime, suggesting that alcohol outlets have direct effects on crime in conjunction with people's routine activity. However, some scholars have offered an alternative mechanism that is worth noting. Some previous studies have found that alcohol outlets are often concentrated in the disadvantaged neighborhoods (Gorman and Speer 1997; Jones-Webb et al. 2008). As a potential explanation, Nielsen et al. (2010) argued that socially disorganized neighborhoods themselves may lead to the concentration of alcohol outlets. This framework suggests that disadvantaged neighborhoods lack the informal social control mechanisms to influence where alcohol outlets are established (Nielsen et al. 2010; Wilson 1996). This view indicates the potential for a selection effect. That is, neighborhood conditions influence where alcohol outlets are established or maintained. However, my results above suggest that alcohol outlets have

effects independent of social disorganization characteristics. At the same time, the social disorganization variables generally have larger effects on street robbery than the alcohol outlet variables. Future research might test for interaction effects between social disorganization and alcohol outlets to explore further, for example, whether the presence of alcohol outlets may amplify the street robbery incidents in socially disorganized neighborhoods, and whether the presence of alcohol outlets may obstruct the crime controlling effects of social organization.

A second alternative explanation is that bars and other alcohol outlets themselves may contribute to the disorganization of the neighborhoods. For example, intoxicated people hanging around bars may be seen as signs of disorder, which would decrease the informal social control mechanism of the neighborhood by increasing the fear of crimes (Roman et al. 2009). It can also be argued that bars and other on-premise alcohol outlets may weaken constraints on the normative conduct because of alcohol consumption (Parker and Rebhun 1995). This suggests that bars and other alcohol outlets themselves are disorganized and have a weakened informal social control mechanism, which in turn contributes to higher violent incidents such as assaults in and around these outlets. This view is consistent with the disorder literature (e.g., Sampson 2012; St. Jean 2007; Wilson and Kelling 1982). This alternative framework differs from routine activity understanding of how alcohol outlets influence street crime.

I am unable to test these alternative frameworks for two reasons. First, examining the selection of alcohol outlet establishments by the level of social disorganization requires longitudinal data. I do not have access to longitudinal police data and alcohol-outlet

establishment data. Second, testing whether alcohol outlets may induce disorder and fear of crime requires the use of self-report data that measure residents' fear of crime or perceptions of disorder. To my knowledge, there has not been any survey done that asks these questions in the city of the current study.

Putting Alcohol Outlets in Place

Despite these limitations, the current study finds some support for the unique effects of alcohol outlets on street robbery. In addition, this study demonstrates the need for carefully considering the time of the crime and land use covariates as well as disaggregating alcohol outlets into different types. In so doing, this study also addresses the theoretical and empirical limitations of previous studies. Previous studies often fail to incorporate important theoretical assumptions and predictions about people's routine activities by not taking into account the time of day in their analyses. Previous studies have also paid scant attention to the empirical challenge: high correlations between alcohol outlets and other land use variables which potentially mask or water down their unique effects. In other words, because alcohol outlets co-exist with other criminogenic land uses in a given place, it is difficult to tease out the unique effects. My analyses explicitly address the limitations of previous studies and support the hypothesis that alcohol outlets are criminogenic places. I also proposed theoretically-based modeling strategies that take into account both time of day and covariates of alcohol outlets. Considering different types of alcohol outlets, the time of day, and covariates is an important step toward putting alcohol outlets in their right place in the literature of criminogenic places.

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APPENDICES

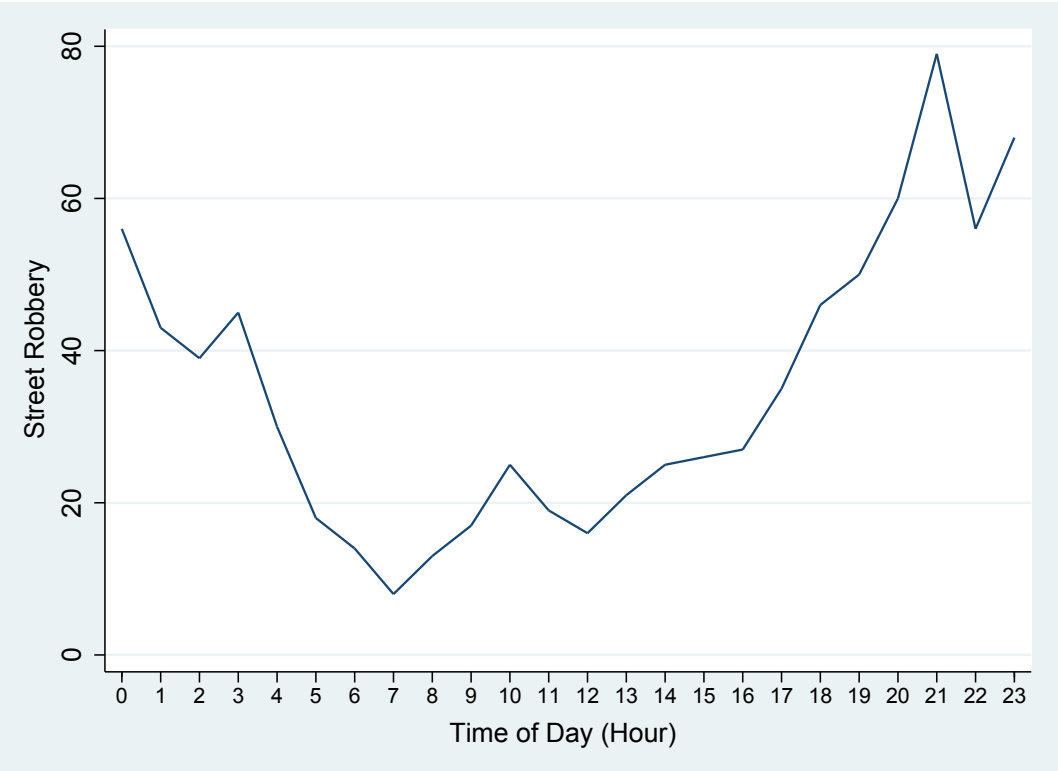

Figure 1. Street Robbery Incidents by Time of Day at the Block Group Level (n=836)

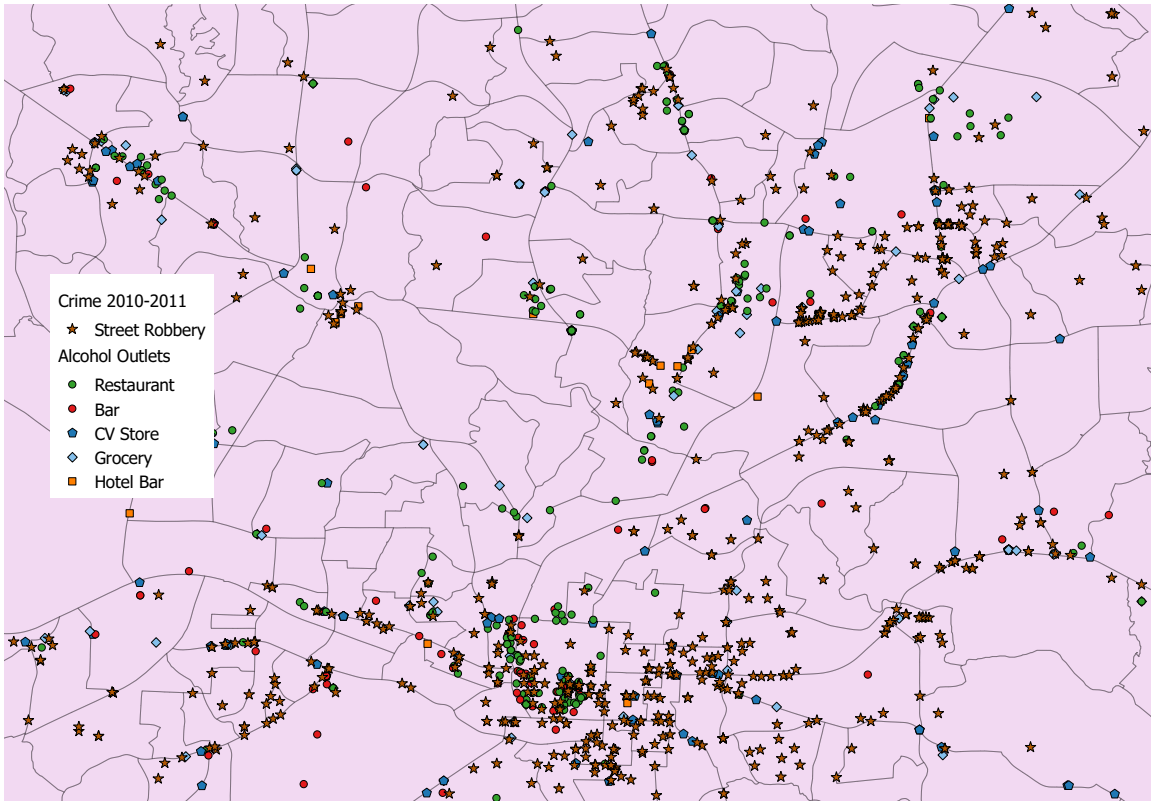

Figure 2. Map of Street Robbery Incidents and Alcohol Outlets in Block Groups

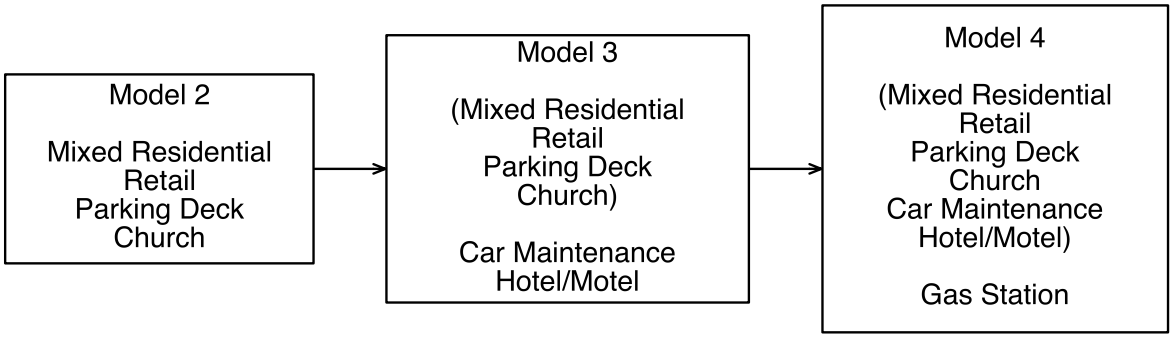

Figure 3. Land Use Covariates of Alcohol Outlets (Corresponding to Table 9)

Table 1. Street Robbery Time Stamp Descriptions

Street Robbery Time Stamp	Time Designation	# of Incidents
All Time Street Robbery	Sum of all street robbery incidents	834
Day Time Street Robbery	Sum of all street robbery incident that happened between 5:00 a.m.-3:59 p.m.	201
Early Evening Street Robbery	Sum of all street robbery incidents that happened between 4:00 p.m.-8:59 p.m.	218
Night Time Street Robbery	Sum of all street robbery incidents that happened between 9:00 p.m.-11:59 p.m.	203
Late Night Street Robbery	Sum of all street robbery incidents that happened between 12:00-4:59 a.m.	212

Table 2. Variable Descriptions

Variables	Measures at Block Group	Data Source
Alcohol Outlets		
Total Alcohol Outlets	Number of Bar, Restaurant, Convenience Store, Grocery Store, Hotel Bar, and Liquor Store	2010 Alcohol Control Board (ABC)
On-Premise Outlets	Number of Bar and Restaurant	ABC
Off-Premise Outlets	Number of Convenience Store, Grocery Store, and Liquor Store	ABC
Bars	Number of bar and social bar clubs with liquor license	ABC
Restaurants	Number of restaurants with liquor license	ABC
Convenience Stores	Number of convenience stores with liquor license	ABC
Grocery Stores	Number of grocery stores with liquor license	ABC
Hotel Bars	Number of hotels with with liquor license	ABC
Liquor Stores	Number of liquor stores	2010 ReferenceUSA Historical Business
Social Disorganization		
Concentrated Disadvantage Index	Sum of z-scores of (1) % poor families, (2) % single mothers with children, and (3) % unemployed	2010 Decennial Census (Census)
Residential Instability Index	Average of z-scores of (1) % moved after year 2005, and (2) % rental housing	2006-2010 American Community Survey

Blau's Heterogeneity Index	One minus the sum of squared proportions of following races: White, Black, Hispanic, Asian, Native American, and Other race	Census
Distance to City Center	Distance from the centroid of a city center to a centroid of a block group, unit in kilometer	Census
Total Population	Total population	Census
Land Use		
Single Family Units	Number of single family unit	2010 Tax Assessor's Data (Tax)
Dual Family Units	Number of dual family unit	Tax
Family Units	Number of family unit	Tax
Mixed Residential Buildings	Number of mixed residential buildings	Tax
Retail	Number of retail stores	Tax
Offices	Number of office spaces	Tax
Banks	Number of banks	Tax
Parking Decks	Number of parking decks	Tax
Gas Stations	Number of gas stations	Tax
Car Maintenance	Number of car maintenance establishments	Tax
Hotels/Motels	Number of hotels and motels	Tax
Churches	Number of churches	Tax
Industrial	Number of industrial related establishments	Tax

Table 3. Descriptive Statistics

Variables	N	Mean	S.D.	Min.	Max.	IQR
Street Robberies						
All Time Street Robbery	232	3.60	5.78	0	52	5
Day Time Street Robbery	232	0.87	1.77	0	16	1
Early Evening Street Robbery	232	0.94	1.66	0	13	1
Night Time Street Robbery	232	0.88	1.55	0	11	1
Late Night Street Robbery	232	0.91	1.94	0	18	1
Street Robbery Spatial Lags						
All Time Street Robbery Lag	232	3.90	4.07	0	20.75	4.65
Day Time Street Robbery Lag	232	1.02	1.22	0	6.75	1.17
Early Evening Street Robbery Lag	232	1.01	1.01	0	5.25	1.3
Night Time Street Robbery Lag	232	0.91	0.91	0	4.25	1.21
Late Night Street Robbery Lag	232	0.96	0.96	0	7.67	1.22
Alcohol Outlets						
Bar	232	0.45	1.64	0	21	1[a]
Restaurant	232	1.54	3.95	0	47	1
Convenience Store	232	0.68	1.33	0	8	1
Grocery Store	232	0.59	0.95	0	6	1
Hotel Bar	232	0.09	0.43	0	4	1[a]
Liquor Store	232	0.08	0.28	0	2	1[a]
Social Disorganization						
Concentrated Disadvantage Index	232	-0.21	0.89	-2.327	4.36	0.94
Blau's Heterogeneity Index	232	0.44	0.19	0.045	0.72	0.29
Residential Instability Index	232	0.63	1.14	-1.742	3.35	1.2
Distance to City Center	232	8.13	4.59	0	20.64	6.89

Total Population	232	1896.24	1194.17	30	8745	1070
Land Use						
Single Family Unit	232	513.17	396.23	0	2719	389
Dual Family Unit	232	9.44	15.09	0	71	15
Family Unit	232	2.74	7.73	0	81	2
Mixed Residential Building	232	0.65	2.04	0	23	1
Retail	232	4.26	10.39	0	131	5
Office	232	17.07	34.39	0	246	16.5
Bank	232	0.51	0.98	0	6	1
Parking Deck	232	0.49	2.15	0	26	1[a]
Gas Station	232	0.12	0.36	0	2	1[a]
Car Maintenance	232	2.58	5.82	0	50	2
Hotel/Motel	232	0.36	1.18	0	9	1[a]
Church	232	1.66	2.39	0	23	3
Industrial	232	9.16	21.83	0	138	5

NOTE: IQR= Interquartile Range
a. The actual IQR is 0, but adjusted for 1 for interpretation purpose. IQR of 0 indicates that most census block groups have zero number of these establishments.

Table 4. Moran's I for Street Robbery by Time Stamp

Street Robbery Time Stamp	Moran's I[a]	Z scores[b]
All Time Street Robbery	0.3406***	9.7523
Day Time Street Robbery	0.2384***	6.5317
Early Evening Street Robbery	0.2924***	7.8063
Night Time Street Robbery	0.2461***	6.7920
Late Night Street Robbery	0.1840***	5.5973

a. Asterisks are for pseudo p-values obtained from GeoDa.
b. Approximate values based on 999 purmutations in GeoDa
* p<.05; ** p<.01; *** p<.001

Table 5. Bivariate Correlation Matrix (N=232; Block Group)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)
(1) All Time Street Robbery	1.00																															
(2) Day Time Street Robbery	0.80*	1.00																														
(3) Evening Street Robbery	0.87*	0.63*	1.00																													
(4) Night Time Street Robbery	0.83*	0.53*	0.66*	1.00																												
(5) Late Night Street Robbery	0.84*	0.51*	0.61*	0.64*	1.00																											
(6) Total Alcohol Outlets	0.55*	0.56*	0.50*	0.39*	0.40*	1.00																										
(7) On-Premise Alcohol Outlets	0.53*	0.53*	0.46*	0.40*	0.38*	0.95*	1.00																									
(8) Off-Premise Alcohol Outlets	0.38*	0.38*	0.40*	0.19*	0.28*	0.67*	0.42*	1.00																								
(9) Bar	0.53*	0.54*	0.42*	0.41*	0.38*	0.84*	0.89*	0.35*	1.00																							
(10) Restaurant	0.50*	0.49*	0.44*	0.38*	0.35*	0.94*	0.98*	0.41*	0.79*	1.00																						
(11) Convenience Store	0.37*	0.39*	0.34*	0.22*	0.27*	0.56*	0.34*	0.87*	0.37*	0.30*	1.00																					
(12) Grocery Store	0.22*	0.22*	0.28*	0.09	0.15*	0.53*	0.36*	0.73*	0.22*	0.40*	0.37*	1.00																				
(13) Hotel Bar	0.15*	0.09	0.22*	0.05	0.15*	0.25*	0.13*	0.42*	0.03	0.17*	0.22*	0.13*	1.00																			
(14) Liquor Store	0.04	0.01	0.07	0.03	0.00	0.22*	0.19*	0.14*	0.08	0.22*	0.09	0.17*	0.02	1.00																		
(15) Concentrated Disadvantage	0.41*	0.25*	0.40*	0.46*	0.28*	-0.04	-0.07	0.06	-0.03	-0.08*	0.14*	-0.09	0.02	-0.08	1.00																	
(16) Blau's Heterogeneity Index	0.23*	0.11	0.22*	0.28*	0.17*	0.14*	0.09	0.21*	0.11	0.07	0.25*	0.08	0.03	-0.02	0.24*	1.00																
(17) Residential Instability	0.30*	0.13	0.24*	0.38*	0.26*	0.09	0.09	0.04	0.07	0.10	0.05	0.00	0.04	0.16*	0.28*	0.46*	1.00															
(18) Distance to City Center	-0.34*	-0.34*	-0.26*	-0.28*	-0.26*	-0.07	-0.08	-0.01	-0.17*	-0.04	-0.12	0.15*	-0.03	-0.05	-0.33*	0.10	-0.20*	1.00														
(19) Total Population	0.03	-0.01	0.07	0.01	0.02	0.08	0.05	0.11	0.01	0.06	0.05	0.19*	-0.03	-0.03	0.02	0.29*	0.06	0.43*	1.00													
(20) Single Family Unit	-0.09	-0.04	0.01	-0.18*	-0.10	0.07	0.03	0.11	0.03	0.03	0.05	0.20*	-0.05	0.01	-0.19*	0.07	-0.22*	0.40*	0.77*	1.00												
(21) Dual Family Unit	0.32*	0.26*	0.29*	0.22*	0.29*	0.07	0.07	0.02	0.12	0.04	0.06	-0.02	-0.02	0.22*	0.15*	-0.08	0.19*	-0.48*	-0.19*	-0.13*	1.00											
(22) Family Unit	0.26*	0.13	0.19*	0.34*	0.23*	0.01	0.03	-0.03	0.07	0.01	0.02	-0.08	-0.04	0.04	0.17*	0.09	0.25*	-0.21*	-0.03	-0.10	0.30*	1.00										
(23) Mixed Residential Building	0.50*	0.54*	0.42*	0.37*	0.35*	0.68*	0.76*	0.19*	0.73*	0.72*	0.20*	0.12	0.00	0.19*	0.02	0.05	0.16*	-0.27*	-0.03	-0.02	0.25*	0.15*	1.00									
(24) Retail	0.59*	0.59*	0.53*	0.44*	0.40*	0.84*	0.86*	0.40*	0.79*	0.83*	0.34*	0.34*	0.10	0.26*	-0.02	0.14*	0.10	-0.13	0.08	0.09	0.18*	0.08	0.77*	1.00								
(25) Office	0.26*	0.29*	0.23*	0.18*	0.17*	0.46*	0.43*	0.31*	0.37*	0.43*	0.26*	0.23*	0.15*	0.20*	-0.08	0.08	0.09	-0.01	-0.02	-0.03	0.06	-0.02	0.42*	0.42*	1.00							
(26) Bank	0.06	0.15*	0.06	0.03	-0.02	0.29*	0.24*	0.29*	0.10	0.29*	0.16*	0.36*	0.10	0.14*	-0.14*	-0.07	0.11	0.12	0.09	-0.01	0.02	-0.04	0.05	0.18*	0.31*	1.00						
(27) Parking Deck	0.49*	0.50*	0.39*	0.41*	0.34*	0.69*	0.78*	0.18*	0.75*	0.74*	0.15*	0.13*	0.10	0.04	-0.01	0.06	0.11	-0.16*	-0.00	-0.01	0.20*	0.04	0.69*	0.70*	0.36*	0.13*	1.00					
(28) Gas Station	0.20*	0.10	0.23*	0.09	0.23*	0.18*	0.12	0.27*	0.04	0.14*	0.18*	0.19*	0.33*	0.17*	0.06	0.08	0.09	-0.13	-0.01	-0.02	0.16*	-0.03	0.09	0.10	0.13*	0.05	0.08	1.00				
(29) Car Maintenance	0.36*	0.38*	0.31*	0.27*	0.25*	0.46*	0.34*	0.47*	0.34*	0.32*	0.50*	0.25*	0.12	0.24*	0.07	0.22*	0.12	-0.09	0.08	0.05	0.11	0.02	0.29*	0.52*	0.29*	0.12	0.19*	0.19*	1.00			
(30) Hotel/Motel	0.44*	0.46*	0.39*	0.32*	0.28*	0.42*	0.37*	0.36*	0.33*	0.36*	0.30*	0.08	0.59*	0.01	0.01	0.15*	0.08	-0.12	0.01	-0.03	0.02	0.02	0.31*	0.42*	0.29*	0.05	0.31*	0.29*	0.43*	1.00		
(31) Church	0.44*	0.45*	0.42*	0.34*	0.28*	0.43*	0.47*	0.16*	0.51*	0.42*	0.22*	0.06	-0.06	0.01	0.13	-0.02	-0.01	-0.24*	0.02	0.08	0.34*	0.13*	0.50*	0.55*	0.16*	0.01	0.46*	-0.06	0.19*	0.18*	1.00	
(32) Industrial	0.20*	0.25*	0.16*	0.15*	0.10	0.32*	0.23*	0.29*	0.25*	0.21*	0.33*	0.14*	0.02	0.33*	0.01	0.20*	0.13	-0.04	0.08	0.08	0.09	-0.00	0.26*	0.43*	0.26*	0.07	0.15*	0.13	0.79*	0.33*	0.17*	1.00

Table 6. NB-H Models for Total Alcohol Outlets, On-Premise, and Off-Premise

	All Time Street Robbery, Census Block Group (n=232)			
Variables	Total	On-Premise	Off-Premise	On-/Off-Premise
Alcohol Outlets				
Total Alcohol Outlets	0.049***			
	(0.0103)			
On-Premise		0.0507***		0.0333***
		(0.0135)		(0.00916)
Off-Premise			0.172***	0.125***
			(0.0333)	(0.0325)
Social Disorganization				
Concentrated Disadvantage	0.391***	0.382***	0.358***	0.374***
	(0.0870)	(0.0902)	(0.0858)	(0.0826)
Blau's Heterogeneity	1.415**	1.615***	1.111*	1.163**
	(0.437)	(0.445)	(0.450)	(0.439)
Residential Instability	0.199**	0.184**	0.250***	0.219**
	(0.0664)	(0.0678)	(0.0673)	(0.0668)
Spatial Lag	0.130***	0.135***	0.126***	0.122***
	(0.0206)	(0.0216)	(0.0206)	(0.0198)
Intercept	-0.585*	-0.600*	-0.599**	-0.611**
Overdispersion Parameter				
Distance to City Center	-0.0261	-0.0297	-0.128*	-0.00937
	(0.0636)	(0.0658)	(0.0562)	(0.0647)
Total Population	-0.000439	-0.000379	0.0000845	-0.000325
	(0.000502)	(0.000453)	(0.000175)	(0.000420)
Concentrated Disadvantage	-0.128	-0.150	-0.279	-0.124
	(0.181)	(0.179)	(0.172)	(0.183)
Blau's Heterogeneity	-1.451	-1.393	-0.703	-1.534
	(1.148)	(1.096)	(1.094)	(1.144)

lnAlpha Intercept	1.050	1.046	0.491	0.748
AIC	4.053	4.099	4.068	4.029
Log Likelihood	-459.15797	-464.48697	-460.91486	-455.3904
Pseudo R^2	0.126	0.116	0.123	0.133

Unstandardized coefficient, standard errors in parentheses
* p<.05; ** p<.01; *** p<.001 (two-tailed); † p<0.05 (one-tailed)

Table 7. Alcohol Outlets and Social Disorganization Only Models Predicting Street Robberies by Time Stamps (Omitting Restaurants and Liquor Stores)

Variables	All Time Street Robbery		Day Time Street Robbery		Early Evening Street Robbery		Night Time Street Robbery		Late Night Street Robbery	
	b	IQR Effect	b	IQR Effect	b	IQR Effect	b	IQR Effect	b	IQR Effect
Alcohol Outlets										
Bar	0.112***	0.112	0.123***	0.123	0.117***	0.117	0.127***	0.127	0.103***	0.103
	(0.0285)		(0.0252)		-0.017		-0.0226		-0.021	
Restaurant										
Convenience Store	0.103†	0.103	0.190**	0.190	0.0359	0.036	0.000275	0.0003	0.215*	0.215
	(0.0539)		(0.0625)		(0.0573)		(0.0640)		(0.0970)	
Grocery Store	0.141*	0.141	0.128	0.128	0.259***	0.259	0.0797	0.080	-0.0303	-0.030
	(0.0670)		(0.104)		(0.0734)		(0.0947)		(0.131)	
Hotel Bar	0.248†	0.248	0.114	0.114	0.242*	0.242	0.132	0.132	0.330	0.330
	(0.131)		(0.175)		(0.117)		(0.155)		(0.238)	
Liquor Store[a]										
Social Disorganization										
Concentrated Disadvantage	0.367***	0.345	0.289**	0.272	0.429***	0.403	0.475***	0.447	0.244*	0.240
	(0.0873)		(0.0974)		(0.112)		(0.0967)		(0.107)	
Blau's Heterogeneity	1.175**	0.341	0.101	0.029	1.466*	0.425	2.026**	0.588	0.666	0.193
	(0.437)		(0.667)		(0.596)		(0.759)		(0.662)	
Residential Instability	0.228**	0.274	-0.0458	-0.055	0.107	0.128	0.267**	0.320	0.418***	0.502
	(0.0694)		(0.113)		(0.0869)		(0.0904)		(0.122)	
Spatial Lag	0.124***	0.577	0.289***	0.338	0.358***	0.465	0.297**	0.359	0.304**	0.371
	(0.0208)		(0.0826)		(0.0821)		(0.102)		(0.102)	
Intercept	-0.542*		-0.968*		-1.781***		-1.996***		-1.478***	
Overdispersion Parameter										
Distance to City Center	-0.00733		0.198*		0.0389		0.227		0.229*	
	(0.0660)		(0.0830)		(0.132)		(0.160)		(0.101)	
Total Population	-0.000494		-0.000749		-0.00252***		0.00000474		-0.00140*	
	(0.000606)		(0.000520)		(0.000390)		(0.000351)		(0.000607)	
Concentrated Disadvantage	-0.0988		-0.808*		0.139		-0.432		0.221	
	(0.193)		(0.356)		(0.369)		(0.395)		(0.285)	

Blau's Heterogeneity	-1.262	-2.167	-1.154	-8.078*	2.996
	(1.286)	(1.634)	(2.357)	(3.595)	(3.446)
lnAlpha Intercept	0.850	1.000	2.800*	1.620	-0.705
AIC	4.04	2.19	2.25	2.12	2.29
Log Likelihood	-455.046	-240.213	-247.523	-231.703	-251.064
Pseudo R^2	0.134	0.122	0.151	0.101	0.111

Note. Standard errors in parentheses.
a. Not included in the model because of small coefficient and nonsignificance.
* p<.05; ** p<.01; *** p<.001 (two-tailed); † p<0.05 (one-tailed)

Table 8. Alcohol Outlets and Social Disorganization Only Models Predicting Street Robberies by Time Stamps (Omitting Bars and Liquor Stores)

Variables	All Time Street Robbery		Day Time Street Robbery		Early Evening Street Robbery		Night Time Street Robbery		Late Night Street Robbery	
	b	IQR Effect	b	IQR Effect	b	IQR Effect	b	IQR Effect	b	IQR Effect
Alcohol Outlets										
Bar										
Restaurant	0.0466***	0.047	0.0540***	0.054	0.0529***	0.053	0.0577***	0.058	0.0450***	0.045
	(0.0130)		(0.0120)		(0.00774)		(0.00966)		(0.00967)	
Convenience Store	0.135**	0.135	0.216***	0.216	0.0758	0.076	0.0350	0.035	0.235*	0.235
	(0.0498)		(0.0622)		(0.0556)		(0.0628)		(0.0924)	
Grocery Store	0.0885	0.089	0.0756	0.076	0.185*	0.185	0.00916	0.009	-0.0705	-0.071
	(0.0734)		(0.112)		(0.0738)		(0.0936)		(0.129)	
Hotel Bar	0.185	0.185	0.0836	0.084	0.166	0.166	0.0575	0.058	0.304	0.304
	(0.133)		(0.180)		(0.112)		(0.152)		(0.246)	
Liquor Store[a]										
Social Disorganization										
Concentrated Disadvantage	0.365***	0.343	0.301**	0.283	0.441***	0.415	0.475***	0.447	0.241*	0.227
	(0.0853)		(0.0989)		(0.113)		(0.0901)		(0.106)	
Blau's Heterogeneity	1.177**	0.341	0.117	0.324	1.457*	0.423	1.983**	0.575	0.693	0.201
	(0.441)		(0.672)		(0.587)		(0.735)		(0.662)	
Residential Instability	0.220**	0.264	-0.0406	0.049	0.0920	0.110	0.263**	0.316	0.440***	0.528
	(0.0680)		(0.115)		(0.0871)		(0.0906)		(0.119)	
Spatial Lag	0.124***	0.577	0.292***	0.342	0.350***	0.455	0.269**	0.325	0.314**	0.383
	(0.0201)		(0.0876)		(0.0827)		(0.0964)		(0.103)	
Intercept	-0.545*		-0.997*		-1.757***		-1.923***		-1.529***	
Overdispersion Parameter										
Distance to City Center	-0.00610		0.191*		0.0307		0.265†		0.214*	
	(0.0639)		(0.0821)		(0.138)		(0.141)		(0.0927)	
Total Population	-0.000323		-0.000801		-0.00274***		-0.0000752		-0.00144*	
	(0.000415)		(0.000663)		(0.000267)		(0.000363)		(0.000591)	
Concentrated Disadvantage	-0.133		-0.768*		0.118		-0.479		0.175	
	(0.184)		(0.341)		(0.386)		(0.398)		(0.281)	

Blau's Heterogeneity	-1.370	-1.957	-0.688	-8.166*	3.276
	(1.183)	(1.663)	(2.411)	(3.286)	(3.292)
lnAlpha Intercept	0.660	1.076	2.870*	1.537	-0.671
AIC	4.05	2.2	2.25	2.11	2.29
Log Likelihood	-455.6039	-241.0486	-247.54023	-231.20971	-251.6915
Pseudo R^2	0.133	0.119	0.15	0.102	0.108

Note. standard errors in parentheses.
a. Not included in the model because of small coefficient and nonsignificance.
* p<.05; ** p<.01; *** p<.001 (two-tailed); † p<0.05 (one-tailed)

Table 9. Analysis of Covariates of Alcohol Outlets (Bar Only)

Variables	All Time Street Robbery (n=232)				
	Base	Model 1	Model 2	Model 3	Model 4
Alcohol Outlets					
Bar *coefficient*	0.112***	0.0425	0.0675*	0.126***	0.114***
(S.E.)	(0.0285)	-0.0675	(0.0264)	-0.0319	-0.0343
Convenience Store	0.103†	0.0387	0.0589	0.102*	0.112*
	(0.0539)	-0.0452	(0.0427)	(0.0517)	(0.0561)
Grocery Store	0.141*	0.177**	0.156*	0.100	0.123†
	(0.0670)	-0.0642	(0.0616)	(0.0699)	(0.0705)
Hotel Bar	0.248†	-0.245†	-0.242	0.180	0.240†
	(0.131)	-0.146	(0.150)	(0.140)	(0.136)
Other Variables[a]					
Land Use					
Mixed Residential		-0.0472			
		-0.0611			
Retail		-0.00117			
		-0.0118			
Office		0.000343	-0.000107	-0.000209	0.000246
		-0.00201	(0.00201)	(0.00227)	(0.00229)
Bank		0.0423	0.0599	0.0621	0.0532
		-0.0674	(0.0663)	(0.0717)	(0.0736)
Parking Deck		0.00553			
		-0.041			
Gas Station		0.216	0.174	0.268	
		-0.146	(0.148)	(0.171)	
Car Maintenance		0.0363*	0.0336†		
		-0.0179	(0.0181)		
Hotel/Motel		0.220***	0.223***		
		-0.053	(0.0555)		
Church		0.0709*			
		-0.0303			
Industrial		-0.0141**	-0.0139**	-0.00274	-0.00246
		-0.00438	(0.00450)	(0.00306)	(0.00313)
Collinearity Diagnostics					

Bar *Tolerance*	0.8347	0.2339	0.6811	0.7504	0.7532
[VIF]	[1.20]	[4.28]	[1.47]	[1.33]	[1.33]
Convenience Store	0.6736	0.5258	0.5837	0.6341	0.6346
	[1.48]	[1.90]	[1.71]	[1.58]	[1.58]
Grocery Store	0.8376	0.6513	0.7188	0.7393	0.7537
	[1.19]	[1.54]	[1.39]	[1.35]	[1.33]
Hotel Bar	0.9403	0.5186	0.5368	0.8433	0.9228
	[1.06]	[1.93]	[1.86]	[1.19]	[1.08]
Mixed Residential		0.2646			
		[3.78]			
Retail		0.1736			
		[5.76]			
Office		0.6731	0.7322	0.7378	0.7402
		[1.49]	[1.37]	[1.36]	[1.35]
Bank		0.7271	0.7508	0.7524	0.7543
		[1.38]	[1.33]	[1.33]	[1.33]
Parking Deck		0.3348			
		[2.99]			
Gas Station		0.8149	0.8326	0.8420	
		[1.23]	[1.20]	[1.19]	
Car Maintenance		0.2526	0.2774		
		[3.96]	[3.60]		
Hotel/Motel		0.4405	0.4499		
		[2.27]	[2.22]		
Church		0.5911			
		[1.69]			
Industrial		0.3453	0.3497	0.8157	0.8199
		[2.90]	[2.86]	[1.23]	[1.22]

NOTE: Model Portion: Unstandardized coefficients in the models. Standard errors in parentheses.
Collinearity Diagnostics Portion: Tolerance statistics. VIF in brackets.
a. Other variables not shown in the models are social disorganization variables (concentrated poverty, Blau's heterogeneity index, and residential instability index), spatial lag, and overdispersion parameters (distance to city center, total population, concentrated poverty, and Blau's heterogeneity index).
* p<.05; ** p<.01; *** p<.001 (two-tailed); † p<0.05 (one-tailed)

Table 10. Analysis of Covariates, Adding Housing Land Use Variables

		All Time Street Robbery (n=232)			
Variables		Base	Model 1	Model 2	Model 3
Alcohol Outlets					
Bars	*coefficient*	0.114***	0.104**	0.104**	0.105**
	(S.E.)	(0.0343)	(0.0354)	(0.0356)	(0.0331)
Convenience Stores		0.112*	0.107*	0.107*	0.0994†
		(0.0561)	(0.0525)	(0.0526)	(0.0517)
Grocery Stores		0.123†	0.135†	0.135†	0.0967
		(0.0705)	(0.0707)	(0.0710)	(0.0710)
Hotel Bars		0.240†	0.270*	0.270*	0.291*
		(0.136)	(0.134)	(0.134)	(0.134)
Other Variables[a]					
Land Use					
Office		0.000246	-0.000733	-0.000731	-0.000172
		(0.00229)	(0.00230)	(0.00230)	(0.00228)
Banks		0.0532	0.0835	0.0839	0.0814
		(0.0736)	(0.0744)	(0.0751)	(0.0721)
Industrial		-0.00246	-0.00202	-0.00201	-0.00225
		(0.00313)	(0.00312)	(0.00313)	(0.00305)
Dual Family			0.0129**	0.0129**	0.0127**
			(0.00466)	(0.00468)	(0.00468)
Multi Family				0.000311	-0.00185
				(0.00798)	(0.00807)
Single Family					0.000278†
					(0.000147)
Collinearity Diagnostics					
Bars	*Tolerance*	0.7532	0.7482	0.7458	0.7457
	[VIF]	[1.33]	[1.34]	[1.34]	[1.34]
Convenience Stores		0.6346	0.6343	0.6343	0.6339
		[1.58]	[1.58]	[1.58]	[1.58]
Grocery Stores		0.7537	0.6343	0.7481	0.7183
		[1.33]	[1.58]	[1.34]	[1.39]

Hotel Bars	0.9228	0.9208	0.9189	0.9170
	[1.08]	[1.09]	[1.09]	[1.09]
Offices	0.7402	0.7398	0.7393	0.7352
	[1.35]	[1.35]	[1.35]	[1.36]
Banks	0.7543	0.7542	0.7542	0.7528
	[1.33]	[1.33]	[1.33]	[1.33]
Industrial	0.8199	0.8192	0.8145	0.8071
	[1.22]	[1.22]	[1.23]	[1.24]
Dual Family		0.7900	0.7646	0.7646
		[1.27]	[1.31]	[1.31]
Multi Family			0.8104	0.8096
			[1.23]	[1.24]
Single Family				0.8269
				[1.21]

NOTE: Model Portion: Unstandardized coefficients in the models. Standard errors in parentheses.
Collinearity Diagnostics Portion: Tolerance statistics. VIF in brackets.
a. Other variables not shown in the models are social disorganization variables (concentrated poverty, Blau's heterogeneity index, and residential instability index), spatial lag, and overdispersion parameters (distance to city center, total population, concentrated poverty, and Blau's heterogeneity index).
* p<.05; ** p<.01; *** p<.001 (two-tailed); † p<0.05 (one-tailed)

Table 11. Reduced Models by Time Stamps

Variables	Day Time Street Robbery		Early Evening Street Robbery		Night Time Street Robbery		Late Night Street Robbery	
	b	IQR Effect	b	IQR Effect	b	IQR Effect	b	IQR Effect
Alcohol Outlets								
Bar							0.0857***	0.086
Restaurant							-0.0203	
On-Premise					0.0369***	0.074		
					(0.00664)			
Convenience Store	0.143*	0.143	0.0254	0.025	0.0123	0.012	0.150†	0.150
	(0.0665)		(0.0546)		(0.0598)		(0.0848)	
Grocery Store	0.0689	0.069	0.200**	0.200	0.0477	0.048	0.0510	0.051
	(0.119)		(0.0774)		(0.0902)		(0.126)	
Hotel Bar	0.126	0.126	0.326**	0.326	0.115	0.115	0.346†	0.346
	(0.207)		(0.124)		(0.148)		(0.189)	
Liquor Store[a]								
Social Disorganization								
Concentrated Disadvantage	0.357***	0.336	0.529***	0.497	0.451***	0.424	0.251**	0.236
	(0.0983)		(0.109)		(0.0858)		(0.0957)	
Blau's Heterogeneity	0.605	0.175	1.281*	0.371	2.211**	0.641	0.830	0.241
	(0.701)		(0.627)		(0.744)		(0.673)	

Residential Instability	-0.147	-0.176	0.176†	0.211	0.226*	0.271	0.253*	0.304
	(0.130)		(0.103)		(0.103)		(0.125)	
Land Use								
Busy Place	0.00768*	0.084	0.00878***	0.097				
	(0.00352)		(0.00239)					
Office	0.00130	0.021	-0.00136	-0.022				
	(0.00424)		(0.00287)					
Bank	0.253†	0.253	0.102	0.102				
	(0.140)		(0.109)					
Industrial	0.000689	0.003	-0.00337	-0.017				
	(0.00503)		(0.00397)					
Dual Family Unit	0.00929	0.139	0.0144**	0.216	0.00769	0.115	0.0169**	0.254
	(0.00663)		(0.00496)		(0.00552)		(0.00560)	
Multi Family Unit	0.00462	0.009	0.00462	0.009	0.0132†	0.026	0.00888	0.018
	(0.0126)		(0.00846)		(0.00705)		(0.0128)	
Single Family Unit	0.0000134	0.005	0.000652*	0.254	-0.000130	-0.051	0.000139	0.054
	(0.000295)		(0.000255)		(0.000306)		(0.000289)	
Spatial Lag	0.267**	0.312	0.276**	0.359	0.217*	0.263	0.164†	0.200
	(0.0821)		(0.0861)		(0.0939)		(0.0844)	
Intercept	-1.381**		-2.232***		-2.028***		-1.546***	
Overdispersion Parameter								
Distance to City Center	0.235**		0.159		0.283†		0.377**	
	(0.0909)		(0.233)		(0.159)		(0.132)	
Total Population	-0.000677†		0.0000653		-0.0000424		-0.000654	
	(0.000381)		(0.000367)		(0.000464)		(0.000458)	
Concentrated Disadvantage	-0.662†		0.415		-0.530		0.281	
	(0.395)		(0.406)		(0.462)		(0.359)	

Blau's Heterogeneity	-2.148	-6.268	-9.168*	-0.952
	(1.786)	(4.483)	(3.570)	(3.529)
lnAlpha Intercept	0.510	-0.133	1.501	-1.219
AIC	2.21	2.22	2.11	2.28
Log Likelihood	-235.84706	-237.42496	-228.27654	-246.90852
Pseudo R^2	0.138	0.185	0.114	0.125

Note. standard errors in parentheses.
a. Not included in the model because of small coefficient and nonsignificance.
* p<.05; ** p<.01; *** p<.001 (two-tailed); † p<0.05 (one-tailed)

Appendix A. Full Collinearity Diagnostics for Models in Table 9

	All Time Street Robbery (n=232)				
Variables	Base	Model 1	Model 2	Model 3	Model 4
Model Portion[a]					
Collinearity Diagnostics					
Bars *Tolerance*	0.8347	0.2339	0.6811	0.7504	0.7532
[VIF]	[1.20]	[4.28]	[1.47]	[1.33]	[1.33]
Convenience Stores	0.6736	0.5258	0.5837	0.6341	0.6346
	[1.48]	[1.90]	[1.71]	[1.58]	[1.58]
Grocery Stores	0.8376	0.6513	0.7188	0.7393	0.7537
	[1.19]	[1.54]	[1.39]	[1.35]	[1.33]
Hotel Bars	0.9403	0.5186	0.5368	0.8433	0.9228
	[1.06]	[1.93]	[1.86]	[1.19]	[1.08]
Concentrated Disadvantage	0.7667	0.6601	0.6907	0.6921	0.6921
	[1.30]	[1.51]	[1.45]	[1.44]	[1.44]
Blau's Heterogeneity	0.6553	0.6624	0.6966	0.7024	0.7024
	[1.53]	[1.51]	[1.44]	[1.42]	[1.42]
Residential Instability	0.6504	0.6642	0.6857	0.6872	0.6885
	[1.54]	[1.51]	[1.46]	[1.46]	[1.45]
Mixed Residential		0.2646			
		[3.78]			
Retail		0.1736			
		[5.76]			
Offices		0.6731	0.7322	0.7378	0.7402
		[1.49]	[1.37]	[1.36]	[1.35]
Banks		0.7271	0.7508	0.7524	0.7543
		[1.38]	[1.33]	[1.33]	[1.33]
Parking Decks		0.3348			
		[2.99]			
Gas Stations		0.8149	0.8326	0.8420	
		[1.23]	[1.20]	[1.19]	
Car Maintenance		0.2526	0.2774		

	[3.96]	[3.60]		
Hotels/Motels	0.4405	0.4499		
	[2.27]	[2.22]		
Churches	0.5911			
	[1.69]			
Industrial	0.3453	0.3497	0.8157	0.8199
	[2.90]	[2.86]	[1.23]	[1.22]

NOTE: Tolerance statistics. VIF in brackets.
a. Model portion omitted. See Table 9 for the model portion.

Appendix B. Analysis of Covariates, Adding Land Use Variables Individually

	All Time Street Robbery										
Variables	Base	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Alcohol Outlets											
Bars	0.112***	0.0760	0.0418	0.109**	0.111***	0.0925	0.118***	0.103***	0.110***	0.0493	0.117***
	(0.0285)	(0.0732)	(0.0661)	(0.0336)	(0.0291)	(0.0653)	(0.0258)	(0.0285)	(0.0293)	(0.0440)	(0.0291)
Restaurants											
Convenience Stores	0.103	0.108*	0.109*	0.102	0.104	0.108	0.0939	0.0881	0.102	0.0951	0.110*
	(0.0539)	(0.0548)	(0.0528)	(0.0538)	(0.0544)	(0.0560)	(0.0501)	(0.0546)	(0.0534)	(0.0521)	(0.0553)
Grocery Stores	0.141*	0.146*	0.119	0.140*	0.124	0.142*	0.125	0.135*	0.147*	0.160*	0.138*
	(0.0670)	(0.0685)	(0.0701)	(0.0669)	(0.0708)	(0.0675)	(0.0655)	(0.0663)	(0.0684)	(0.0673)	(0.0667)
Hotel Bars	0.248	0.249	0.223	0.242	0.243	0.239	0.188	0.234	0.221	0.269*	0.249
	(0.131)	(0.131)	(0.131)	(0.135)	(0.131)	(0.132)	(0.137)	(0.131)	(0.141)	(0.128)	(0.130)
Liquor Stores[a]											
Social Disorganization[b]											
Land Use											
Mixed Residential		0.0331									
		(0.0629)									
Retail			0.0122								
			(0.0105)								
Offices				0.000397							
				(0.00216)							
Banks					0.0551						
					(0.0708)						
Parking Decks						0.0150					
						(0.0457)					
Gas Stations							0.242				
							(0.168)				
Car Maintenance								0.0124			

								(0.0132)			
Hotels/Motels									0.00340		
									(0.00720)		
Churches										0.0635	
										(0.0329)	
Industrial											-0.00234
											(0.00304)
Spatial Lag	0.124***	0.122***	0.119***	0.125***	0.124***	0.124***	0.122***	0.121***	0.121***	0.121***	0.126***
	(0.0208)	(0.0212)	(0.0208)	(0.0208)	(0.0206)	(0.0206)	(0.0202)	(0.0211)	(0.0212)	(0.0198)	(0.0211)
Intercept	-0.542*	-0.563*	-0.528*	-0.546*	-0.573*	-0.541*	-0.525*	-0.518*	-0.534*	-0.697**	-0.552*
Collinearity Diagnostics											
Bars	*Tolerance*	0.3848	0.3353	0.7607	0.8347	0.3461	0.8336	0.8092	0.8232	0.6304	0.8229
	[VIF]	[2.60]	[2.98]	[1.31]	[1.20]	[2.89]	[1.20]	[1.24]	[1.21]	[1.59]	[1.22]
Restaurants											
Convenience Stores		0.6633	0.6699	0.6683	0.6678	0.6355	0.6722	0.5923	0.6736	0.6718	0.6401
		[1.51]	[1.49]	[1.50]	[1.50]	[1.57]	[1.49]	[1.69]	[1.48]	[1.49]	[1.56]
Grocery Stores		0.8375	0.7765	0.8269	0.7547	0.8373	0.8222	0.8340	0.8284	0.8360	0.8375
		[1.09]	[1.29]	[1.21]	[1.33]	[1.19]	[1.22]	[1.20]	[1.21]	[1.20]	[1.19]
Hotel Bars		0.9403	0.9302	0.9278	0.9388	0.9148	0.8583	0.9399	0.8619	0.9316	0.9376
		[1.03]	[1.08]	[1.08]	[1.07]	[1.09]	[1.17]	[1.06]	[1.16]	[1.07]	[1.07]
Mixed Residential		0.3972									
		[2.52]									
Retail			0.3189								
			[3.14]								
Offices				0.8029							
				[1.25]							
Banks					0.7986						
					[1.25]						
Parking Decks						0.3964					
						[2.52]					
Gas Stations							0.8515				
							[1.17]				

Car Maintenance	0.6867			
	[1.46]			
Hotels/Motels		0.8445		
		[1.18]		
Churches			0.6865	
			[1.46]	
Industrial				0.8406
				[1.19]

NOTE: Unstandardized coefficients in the models. Standard errors in parentheses. Tolerance statistics in the collinearity diagnostics portion of the table. VIF in brackets.

a. Not included in the model because of small coefficient and non significance.

b. Included in the models, but coefficients not shown.

* p<.05; ** p<.01; *** p<.001 (two-tailed); † p<0.05 (one-tailed)