WHAT'S HOT AND WHAT'S NOT: THE EFFECTS OF INDIVIDUAL FACTORS ON THE IDENTIFICATION OF HOT AND COOL CRIME SPOTS

by

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DEDICATION

To all of the family and friends who supported and encouraged me along the way.

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ABSTRACT

WHAT'S HOT AND WHAT'S NOT: THE EFFECTS OF INDIVIDUAL FACTORS ON THE IDENTIFICATION OF HOT AND COOL CRIME SPOTS

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Theoretical arguments suggest that crime escalates in disadvantaged and disorderly areas because these areas contain cues of danger and safety that signal individuals to stay away, thus reducing effective guardianship, a powerful protective factor against crime. Yet, there is very little knowledge on how perceptions of crime places translate into avoidance or withdrawal behaviors. Moreover, there is limited knowledge of how individual characteristics inform and influence these perceptions. The purpose of this study is twofold. First, this study seeks to understand the accuracy with which people can identify crime hot spots and cool spots within their community. Second, this study will examine the influence of individual predictors on respondents' abilities to identify crime and non-crime locations within the two study neighborhoods. Specifically, individual level predictors of individual demographics, perceptions of crime and disorder, and neighborhood familiarity and tenure are tested. Study measures are derived using two data sources including cognitive maps administered to active community members

(N=168) through the Communities Problems and Issues Survey (CPIS) and calls for service to the Trinidad and Tobago Emergency Response System (E-999). Accuracy and the influence of individual predictors are tested using a mix of analytic techniques including descriptive diagnostics, t-tests, zero-inflated count regression analysis and ordinal logistic regression. Overall, the study supports past perception of crime research by determining that respondents are not accurate in identifying crime hot spots. Additionally, when testing the individual predictors that influence accuracy, two factors, gender and neighborhood familiarity, have a strong influence on whether respondents include crime hot spots in the areas they consider unsafe or dangerous. The study concludes with a discussion of the study's implications for both practice and research.

CHAPTER 1: INTRODUCTION

In 1974, David Ley wrote, "The power to discriminate between…a safe and dangerous space is assimilated at an early age. Survival depends on the ability to learn safe [spatial] configurations" (p. 212). Although Ley does not clarify the meaning of danger and survival, his statement mimics common beliefs about crime areas. Many logical arguments suggest that people assess whether a location is good or bad and they use this knowledge to maneuver around and avoid bad places. Additionally, many propose that these negative assessments about places can lead to withdrawal behaviors specifically affecting relationships among residents, weakening the community fabric and informal social controls (Ley, 1974; Wilson & Kelling, 1982; Skogan, 1990; Gilmartin, 2000), possibly leading to increases in crime at these locations.

In many ways, empirical science supports the above assumptions. For instance, several empirical studies illustrate the link between places and crime outcomes (Sherman, et. al, 1989; Sherman & Weisburd, 1995; Weisburd, Yang, & Groff, forthcoming) and places and criminal behavior (Brantingham & Brantingham, 1993). Research also concludes that people's perceptions and interpretations of crime places affect their behaviors toward those places and the people within them (Wilson & Kelling, 1982; Skogan, 1990; Brantingham & Brantingham, 1993; Ferraro, 1995; Gilmartin, 2000).

Although much of the logic behind this larger argument is supported, the fundamental assumption that people know where the dangerous and high crime locations are located is not. To date, studies suggest that people do not do a very good job of identifying problem locations. Instead, these studies tend to find that the areas considered to be problematic are often those which rank high in measures of disadvantage such as a high minority population or areas that rank low in terms of socio-economic status (Rengert & Pelfry, 1997; Matei, et.al., 2000). Although research suggests that people are relatively inaccurate at crime location identification, few studies have focused on the variation and predictors of that accuracy among respondents' accuracy.

For as much as we know about the relationship between crime and place, little is known about the context of crime places and about the way that people interpret and maneuver in and around crime locations. The present study uses an exploratory methodology to answer two questions of concern to perceptions of crime locations. First, it follows past research and addresses how accurate respondents are at identifying and including hot spots in the areas they consider unsafe or dangerous throughout their neighborhood. Second, this study will diagnose the individual level factors that influence respondent accuracy in their assessments.

What is Missing?

Although prior studies have tried to diagnose how well respondents identify crime places, this research is somewhat limited in that tends to examine larger geographies instead of micro-locations, which some scholars argue is the most appropriate unit of analysis for crime and place research (see Sherman, et al, 1989; Sherman & Weisburd, 1995; Oberwittler & Wikstrom, 2009; Groff, et al., 2009, 2010). Specifically, research that measures perceptions of crime places (Ley, 1974; Rengert & Pelfry, 1997; Matei, et. al. 2001) rarely attempts to explain crime concentrations at specific places. Instead, prior studies often examine perceptions as they relate to the overall crime problem; not how they relate to crime geographies. For instance, questions in fear of crime surveys often ask respondents how safe they feel in their neighborhood or at other locations. Yet, respondents are rarely asked to choose the locations that they believe are safe or crime free.

Of the few studies that have tried to understand fear and risk concerns as they relate to geography, most have had a very broad scope considering the micro-nature of crime places. Prior studies examining perceptions of dangerous, risky or crime prone areas have failed to consider the micro-level, or location specific, nature of crime locations and instead examine perceptions using larger macro units such as neighborhoods, communities, or census block groups (Rengert & Pelfry, 1997; Matei, et. al., 2000). Thus, studies in this area often fail to acknowledge specific locations that are undesirable and avoided. Consequently, because research rarely examines specific, undesirable locations in a micro-level context, we know very little about how avoidance and withdrawal behaviors can contribute to proven concentrations of crime within them.

Additionally, past research on perceptions of crime locations (e.g., crime hot spots) has failed to consider how individual factors, like differences in demographics and perceptions, can influence reports of high crime locations. This is surprising considering these differences have been noted in other studies within geography (Lynch, 1960; Downs & Stea, 1973; Golledge, et. al., 1976) and in fear of crime and risk assessment literatures (Garafalo, 1981; Skogan & Maxfield, 1979;). In their book, *Patterns in Crime*, environmental criminologists Paul and Patricia Brantingham note,

> The existence of [perpetual] similarities can be seen best in the research of people who study 'mental maps' or cognitive representations of the objective environment. All have uncovered patterns of group variability. Patterns vary by broad sociodemographic characteristics: knowledge and complexity of images increase with age; are generally more complex for people who work outside of the home; vary by social class; generally uncovering a smaller area for the less mobile, lower socioeconomic groups; and vary directly by length of residence. (1984, p.X)

Essentially, these differences exist; yet they are not adequately tested in research that examines perceptions of crime locations.

Overall, although there is some research testing the predictors of influence on crime location accuracy, it has only gone as far as diagnosing the accuracy with which respondents can identify high crime areas. A few studies have also examined how factors from the environment, such as physical layout and presence of social and physical disorder, can influence perceptions and thus explain differences that might be occurring between perceived hot spots and reality (Nasar & Fisher, 1993). However, these studies have not explored how well respondents identify micro-level problem locations within a selected neighborhood. Furthermore, this body of literature has not yet examined how individual circumstances and psychology might play a role in these outcomes.

The Present Study

The present study is an attempt to both diagnose the accuracy with which respondents include crime hot spots in places they consider dangerous and identify the individual-level factors that influence respondent accuracy. Specifically, I test whether selected individual-level factors, including measures of demographics, perceptions of disorder and crime, and neighborhood familiarity and tenure contribute to respondent perceptions of problematic areas.

This research agenda is important because people's assessments about places conceivably have a great influence on their behaviors within them (Ley, 1974; Gilmartin, 2000). For example, if assessments of a micro-place are negative, the literature tells us that a person is more likely to avoid or withdrawal from that location (Ley, 1974; Gilmartin, 2000). Causally, this can reduce effective guardianship over places and people within them. Reduced guardianship of places and people can ultimately impact crime at places (Cohen & Felson, 1979). As guardianship decreases, opportunities to offend increase and thus crime concentrations at micro-places might also increase.

A rebuttal argument to this suggested process might be that places will have fewer potential victim targets because the idea that the location is a crime hot spot will keep people from those places. However, I argue that targets do not have to be people but can also be objects such as buildings or cars. Moreover, many crime hot spots have residents that live in them or people that pass through them, not knowing anything about their criminal nature. Of course, these populations can also provide potential victims as well.

Study Context

Before we move further into the proposed research idea, it is necessary to comment briefly on the context of the study's location. I will go into this further in Chapter Four; however, it is important to briefly provide some insight into the details of the study setting. Doing so helps illustrate how this study differs from past research as well as sheds some insight into this study's importance.

Data for the current study were collected as part of a reform initiative under the Trinidad and Tobago Police Service Project, contracted by the Trinidad and Tobago Ministry of National Security, to reduce violent crime in Trinidad and Tobago. Under this project, researchers worked with the Trinidad and Tobago Police Service to improve policing and reduce crime in specific areas in the country that were very high in violent crime. During the project a number of efforts were implemented including extensive reform efforts for police training and promotion, a Repeat Offender Programme Unit (ROP) that was established to target problem people within the most violent areas, a community policing unit, and a grass-roots crime and gang violence reduction initiative that involved participation from community leaders and community members.

To give you a feel for the research setting, Trinidad and Tobago is a two-island nation that rests in the southern-most portion of the Caribbean. Trinidad and Tobago is considered to be a wealthier nation within the Caribbean due to its successes in petroleum and natural gas production (CIA Factbook, September, 2008); yet, much of the country lives in poverty and in many of the high crime areas, there are significant squatter populations. To place the geographic size of the country into perspective, combined the islands are approximately 5,128 square kilometers - relative in size to the state of Deleware (CIA Factbook, September, 2008).

Approximately 1.3 million people reside in Trinidad and Tobago. Of these, the majority of residents identify themselves as Indian (40%), African (37.5%) or Mixed (20.5%). The predominant language of Trinidadian and Tobagonians is English. The majority of Trinidad and Tobago residents have not received more than an 11th grade education. The country is religiously diverse, with substantial numbers of people reporting to be predominately Christian (53.6%) and Hindu (22.5%) (CIA Factbook, September, 2008).

Since 1999, the country has experienced dramatic increases in crime, and more specifically violent gun-related crime (Maguire, et. al., 2009). The two Trinidad and Tobago communities used for this study, Belmont and Morvant, are among the top 10 communities in terms of increases in violent crime between 1999 and 2009. This area yields a unique population because the respondents who participated in this study are those that much too often deal with concerns about crime and violence. Researchers have attempted to diagnose the reasons for the violence within these areas citing neighborhood gang disputes or “street violence” as the leading cause for gun use in these areas (Maguire, et. al., 2009). Additionally, Trinidad and Tobago is cited as a major transshipment point for drugs into the United States and Europe (CIA Factbook, September, 2008). While violence in these areas has not been clearly connected to the drug trade, connections have been established that suggest drug trafficking might also play a small role.

Not surprisingly, residents who live in the areas under study have expressed frustration with a number of social problems, one of the top issues being crime. In surveys, interviews, and focus groups with respondents, team members of the crime reduction initiative were able to conclude that residents in these areas are dissatisfied with both crime and with how the police deal with the crime issue. There are often serious allegations of corruption within the Trinidadian government and the Trinidad and Tobago Police Service. Often, residents in these areas claim they cannot trust the police or the government to take care of crime problems, and yet they live in areas where this is a predominate issue. These problems result in low levels of satisfaction and legitimacy, and some respondents have even acknowledged that if they are dealing with a neighborhood crime problem, they turn to informal means, such as gang leaders who control these areas, for support and justice.

The unusual setting for this study allows for the analysis of crime location accuracy. However, any conclusions drawn from this area may have to be taken with caution. Specifically, the theories and concepts that will be tested here have been developed in older democratic nations. Trinidad and Tobago is relatively new democracy, having gained independence just over 50 years ago. Likewise, there are substantial cultural differences that may not be accounted for in this research. Moreover, this study takes place in areas that are considered to be highly controlled by crime groups, like gangs, and therefore cognitions in these areas may differ substantially from those found in developed nations where legitimacy and satisfaction with the police are relatively higher.

Study Organization

Immediately following this introduction is a series of chapters that feature a comprehensive review of the literature that supports the importance of this proposed study, the planned design and methodologies, information on the site and sample selection of the data source that will be used, and the study results and implications. Next is Chapter Two, which reviews the areas of research relevant to this study, supporting the overall study idea. Specifically, I review literature on crime and place, routine activities and guardianship, avoidance and defensive behaviors, and fear of crime. The goal of this review is to identify what has been missing in past studies on identifications of crime locations. The review also includes a necessary discussion of how this study addresses this gap, drawing from ideas in the literature on fear of crime and assessments of risk.

In Chapter Three I present the two research question for this study. Briefly, the first question how well people can identify crime locations in the community. The second question inquires which factors influence variation and accuracy among respondents. A research model that illustrates the proposed predictors of influence is also included here. Several hypothesized relationships for both research questions are presented in this chapter.

The data collection strategies and descriptions of the data used to derive the study variables are discussed in Chapter Four. In addition, I include detailed information on the demographics of Trinidad and Tobago, on the demographics of the communities targeted in this study, and of the study participants. From there, details of the two data sources for the study are reviewed: the Community Problems and Issues Survey and the E-999 Calls for Service Crime Data. Potential issues with each of these datasets are also addressed in this chapter.

Chapter Five reviews the construction of the six dependent variables for this study. Before that discussion, I present descriptive on the overall accuracy for each of the selected crime and non-crime locations. Additionally, I present results to the first research question concerning respondent accuracy in identifying crime locations in their neighborhood. Respondent accuracies of hot and cool crime spots are tested under a number of conditions including which account for time of day and crime type variations.

Chapter Six contains information on each of the study variables and the analysis plan. The independent variables for this study represent three substantive areas, individual demographics, individual perceptions of disorder and crime, and individual reports of neighborhood familiarity and tenure. Additionally, within this chapter I present the descriptive statistics for each of these measures.

In Chapter Seven I present the study results. Based on the form of the dependent measures, two analyses techniques are used. First, I use zero-inflated count regression analyses to test the study predictors for general and violent crime hot spots for both day and night. Then, I use ordinal logistic regression to test the effects of individual demographics, perceptions of disorder and crime, and neighborhood familiarity and tenure on respondent cognitions of crime cool spots. I conclude the chapter with brief conclusions about the findings.

The concluding chapter, Chapter Eight, presents the study findings and their implications. Specifically, I review the study results in the context of crime control and prevention literature. Additionally, I speak to the limitations of the current study. I conclude Chapter Eight with suggestions for future studies.

Conclusion

To sum up, this study addresses two question. First, are respondents accurate in their identification of crime and non-crime locations? Second, what individual level factors, if any, influence crime and non-crime location identification among respondents? The potential implications from this research are twofold. First, the findings may be able to provide some additional explanation as to *why* crime concentrates at places. We know certain environmental factors can explain a great deal of variance among crime places in a city (Weisburd, Yang, & Groff, forthcoming). Overall, if certain individual factors are better predictors of accuracy, then this can tell us something about those populations and their knowledge of the crime environment.

However, conclusions can also be drawn if no individual predictors are found to have a significant effect on the accuracy with which people identify crime hot spots. For instance, it might be determined that there are patterned misses in the identification of crime hot spots that are conditioned by individual factors. Alternatively, the research may find that there is no relationship at all between perceptions of crime locations and individual factors. Either of these outcomes will still allow for useful conclusions and implications concerning crime prevention and reduction efforts.

CHAPTER 2: PEOPLE AND CRIME PLACES

A remaining question related to crime and place studies is *why* crime concentrates at places. Although a good portion of past research has focused mostly on the fundamental step of diagnosing the crime and place phenomenon, very few studies have attempted to explain why. Recently, however, scholars are working toward a comprehensive explanation of the context – or the why – of crime occurrences at specific places. It is in this latter area, the context of crime, where this study finds its potential for a larger contribution to the field of criminology. Specifically, understanding the accuracy with which people can identify crime hot spots can lead to a better understanding of human activity in these places. In turn, understanding individual behaviors within places can lead to explanations about crime concentrations at places.

To help explain the relevance of the present study it is necessary to first review the larger argument for this study's importance. To best explain and support the need for this study, I will begin with a review of the crime and place literature. Crime and place research is reviewed so that we can gain an understanding of the specificity, concentrations, and stability of crime places (between the environment and the people within them). This review is important because these diagnoses suggest that there are other dynamics occurring at these places that foster and facilitate crime that are separate from aggregated measures of the community and neighborhood characteristics.

Second, I review the most relevant theory to aid in understanding crime occurrences at place – routine activity theory. Routine activity theory proposes that there are three elements to every crime, a motivated offender, a suitable target, and the lack of a capable guardian. This theory suggests that we can understand crime concentrations at places through the opportunities that arise with the convergence of these three elements in time and space. The present study is relevant to routine activity in that it illustrates how respondent actions such as avoidance or withdrawal can influence a place.

Further, I review literature concerning the reactions to fear, risk and perceptions of crime. Most often literatures cite that people engage in two primary behaviors, avoidance and withdrawal, in response to fear and risk of victimization. For instance, a person might avoid certain blocks that they deem unsafe or may avoid larger areas all together as a means of controlling potential victimization. Leading works in this area, like Wilson & Kelling's Broken Windows Thesis (1982) and Skogan's Spiral of Decay hypothesis (1990), propose that avoidance and withdrawal lead to more crime because there is a lack of presence and involvement of community members. The key point from this section is that people often engage in avoidance and withdrawal from areas they believe to be crime ridden. This in turn lowers both social and physical guardianship in these areas, a key element of routine activity theory, hypothetically leading to crime occurrences and stability at these locations. A major assumption in all of this is that the areas that people avoid are the areas where there are stable crime places (as with crime hot spots), although this assumption is not broadly tested. Consequently, a goal of this study is to test how accurate respondents are at identifying these actual crime locations.

Once I have reviewed these larger bodies of literature and how this study can make a contribution to each, the literature review will move into a detailed discussion of the work that is directly related to this study, specifically research on perceptions of crime geography. Each of the studies in this section finds that perceptions of crime locations are not necessarily reflective of actual crime locations. In some cases, scholars identify certain factors such as minority populations (Rengert & Pelfrey, 1998; Matei, et. al, 2000) and disorder (Nasar & Fisher, 1993; Doran & Lees, 2003) as influential factors on individual perceptions of problem places. However, this detailed review will also illustrate that many factors, relevant in fear of crime and risk assessment research remain untested.

Finally, I will include a detailed review of the fear of crime literature. The inclusion of the fear of crime review is useful for two reasons. First, none of the other perception of crime location studies has really considered how an individual's characteristics and perceptions can influence their understanding of crime locations. Second, the fear of crime literature is in many instances linked to literatures concerning avoidance and withdrawal behaviors and assessments of risk by individuals (DuBow, et al, 1979; Liska, 1987; Ferraro, 1995). Overall, visiting the fear of crime literature is important because a review of these concepts will serve as a guide to help establish variables of interest that should be included in this study as independent constructs.

Crime and Place

Over the last 20 years there has been a movement in criminology to push the focus of crime studies on places rather than offenders (Sherman, 1995; Weisburd, 2002). Scholars who support this push contend that places are better targets than people for crime prevention efforts. Specifically, since crime is concentrated at stable, non-moving places over time, crime prevention efforts that focus on place will be more successful than those that target offender populations, which constantly move and change (Weisburd, et.al., 2004; Weisburd, 2008). In fact Sherman (1995) notably suggests that we need to be focused on “where done it, not who done it.”

This push to move toward place-based research seems reasonable considering what empirical studies tell us about the crime and place phenomenon. First, we know that geography is consistently related to crime concentrations at the micro level (Pierce, et. al., 1986; Sherman, et. al., 1989; Weisburd, et. al., 2006). In their groundbreaking study, Sherman and colleagues (1989) found that over 50.4% of all calls for police service originate at 3.3% of all places (p. 38). Since then studies that examine crime at place continue to discover this consistency of concentration at small scale places (Weisburd & Green, 1995; Weisburd & Green Mazerolle, 2000; Weisburd, et. al. 2006; Weisburd, Morris, & Groff, 2009).

Second, we know that there is tremendous variability of crime at the micro-level. Groff and colleagues (2009; 2010) find that there is substantial variability in crime concentrations among street segments over time. Oberwittler & Wikstrom (2009) add to these conclusions with their comparative analysis of crime concentrations at both the micro and macro levels of geography. In that study, they find that smaller units of geography are preferable because smaller units are more likely to be homogenous in their environmental characteristics. This finding is important in that factors that are relevant to explaining crime concentrations at place are more homogenous and stable at the micro level.

Third, we know that crime concentrated places are very stable over time (Weisburd, et. al., 2004; Braga, Papachristos, & Hureau, 2009; Groff, Weisburd, & Yang, 2010). In 2004, Weisburd and colleagues determined that even though some street segments had increasing or decreasing trends over time, there was a large amount of stability. They contend that shifts in overall crime rates were driven by a very small number of street segments that experienced dramatic change. They also found that even though overall crime trends in Seattle were decreasing during the time of the study, 2% of street segments experienced crime waves of 46% increase. Thus, although crime decreased overall, certain places in the city, and the people frequently in those places, experienced either chronic high crime problems or substantial crime increases and subsequent victimization.

Additionally, we know that crime is concentrated for specific types of crime including but not limited to drug markets (Weisburd & Green, 1995; 2000), gun violence (Braga, et. al., 2009) and juvenile crime (Weisburd, Morris, & Groff, 2009). For instance, Weisburd & Green Mazerolle (2000) found that just 226 (approximately 5%) of the street segments and intersections in Jersey City, New Jersey, contained drug activity. Moreover, they found that these 226 places were primarily distributed in the southern part of the city (42%) but still showed variance from street block to street block. Similarly, Braga and colleagues (2009) found that 89% of Boston street segments experienced no gun violence and that “volatile concentrations of serious gun violence” incidents occurred at just 3% of street segments between 1980 and 2008. Similarly, Weisburd and colleagues (2009) find that approximately 33% of juvenile crime incidents were located at just 86 street segments and that these concentrations are very stable over time. This is rather astonishing considering that there are over 26,000 street segments in the city of Seattle, where the study was conducted.

Although we seem to know a lot about diagnosing crime and place and have even used this knowledge to inform policy, some argue that there are elements about crime and place about which we know very little. For instance, Weisburd (2002) argues,

> We need to gain a greater understanding of those factors that influence the development of crime in specific contexts….We need to consider why crime develops in a particular place, situation, or organizational context – what criminal career theorists define in terms of offenders as the problem of ‘onset”. We also need to develop knowledge on why some criminal contexts include a very high rate of criminal activity and others experience only a few incidents, or why some include more serious crimes” (p. 208)

Thus, even though we have made considerable efforts in diagnosing the existence and nature of crime at places, we still know very little about the contextual factors and dynamics that exist at these places which foster and sustain criminal activity. Arguably, an understanding of these contextual factors is necessary in order to make great strides in crime prevention efforts because diagnosing and targeting a crime concentrated area only addresses part of the issue. What is needed is an understanding of the various elements that contribute to a crime hot spot's development including the environment as well as person interactions and involvement at these places.

Even though the present study is not a direct examination of crime places, it has the potential to contribute to the *why* argument of crime and place by adding to knowledge concerning individual and community behaviors and their influence on crime places. Specifically, this research will examine how accurate respondents are in identifying hot and cool crime spots within their larger neighborhood. Aside from testing accuracy, this study will also examine how individual factors, like demographics and perceptions of crime and disorder, influence people's ability to identify crime hot and cool locations. This is important for two reasons. First, the accuracy with which people can name high crime locations may differ based on individual differences. For example, younger people may be better able to name crime hot spots than older residents, or those who have lived in the neighborhood longer, would be better able to pinpoint crime areas than those who just moved to the neighborhood. Secondly, it is entirely feasible that people avoid places because they believe crime exists in that location (and it may or may not). Yet, as we have seen with other research (particularly in fear of crime and risk assessment studies), there are many individual and cognitive based factors that influence individual assessments. Understanding these may lead us to a better explanation of why different demographics avoid specific areas, regardless of whether they are high crime.

Opportunity Theories and the Context of Crime Places

Opportunity theories are often used in studies concerning crime and place. Unlike traditional criminological theories, which tend to focus on the reasons why offenders are driven to a path of crime, these theories focus on the situation or opportunity that attracts a person to and that facilitates a crime event. Opportunity theories are especially useful in crime and place research because they make the connection between the opportunities and people to explain the context of crime events.

Rational Choice Theory

The first opportunity theory that is useful to the study of the context of crime places is Rational Choice Theory. Rational Choice Theory is most often used to explain the rational decision process of an offender that leads to the commission of a crime (see Clarke & Cornish, 1985; Cornish & Clarke, 1986). Traditional writings cite that a key premise behind rational choice theory is the cost-benefit of committing a crime to an offender. Essentially a cost-benefit assessment is where the offender decides if the benefit from committing the crime (i.e., money, sex, drugs, etc.) is worth the potential costs of getting caught. Moreover, rational choice theory often argues that offender motivations are explainable through “situational selection”, or instances where offenders have an easy target, a low likelihood of being caught, and a high expected reward (Cornish & Clarke, 1986). Past work also suggests that the rational decisions of offenders are bounded and that decisions for offending often times have to be made with a certain amount of risk or uncertainty.

These same decision frameworks are useful when explaining the behaviors of non-offender populations, which are also a critical element of the context of crime places and the key focus of this study. For instance, instead of the cost-benefit assessment of whether or not to commit a crime, this decision framework is about whether or not a person should travel to these locations. In these cases the benefit of being able to travel to (e.g., desirable restaurant on street block) or through the place (e.g., most convenient route of passage) is weighed against the cost, which is the perceived likelihood of victimization or risk. The application of rational choice theory in this manner is also extendable to the principle of situational selection. Ideally, victims are willing to travel if they perceive a place to have a low risk of vulnerability, a high likelihood of guardianship, and the expected reward of safety or non-victimization. Like traditional applications of rational choice theory, the decisions that residents make are also limited or bounded to the information unique to each person.

Viewing decisions about places through this altered rational choice framework can help diagnose the context of crime places. It may be that certain demographics are more accurate in their perceptions of crime locations. For instance, it could be the case that residents who are more educated are better at identifying crime hot spots. This finding would allow for a better understanding of the influence of education on the assessments of places. The utility of this framework is also extendable to understanding victim trends and populations at crime places. For example, if victims at a known crime location are primarily uneducated and we know that educated residents are better at identifying crime hot spots, and consequently avoiding those locations, it could lead to knowledge about the education trend in victimization.

Routine Activity Theory

Furthermore, Routine Activity Theory is useful to the study of the context of crime places. Routine Activity Theory is unique in that its focus is on explaining the context of the crime event and is not concerned with offender motivations. In routine activity theory, Cohen and Felson (1979) propose that crime occurs when a rational, motivated offender, a suitable target, and the lack of a capable guardian, converge in time and space to provide a crime opportunity for a criminal. Thus, routine activity theory seeks to explain crime occurrences through the actors, time, and place, not though the criminogenic motivations of people. Essentially, they propose that it does not matter why a person wants to commit a crime; instead it is more important to understand the opportunities that exist that allow crime to occur.

Because routine activity theory provides an explanation of how crime occurs at micro places (Eck & Weisburd, 1995), it is entirely relevant when examining assessments and perceptions of crime places. For instance, an assumption of this study is that avoidance and withdrawal behaviors reduce guardianship if residents believe an area is fraught with crime. A decreased physical presence can then lead to decreased involvement among community members. Directly, if people are not physically present bonds with fellow community members are never formed and maintained. These bonds are essentially the establishment of social guardianship through informal social controls.

Therefore, following the propositions within routine activity theory, this study considers respondent behavior to be the key element that influences the absence or presence of crime at a place.

Overall, rational choice and routine activity theories are essential to this study's importance. I propose that like offenders, potential victims and guardians, make assessments about places, just as an offender does. These assessments can inform perceptions of places, leading to negative behaviors, such as avoidance or withdrawal, which can ultimately feed into the crime context of these places. When people engage in avoidance or withdrawal behaviors from a place, the supervision of that place, and the people within it, will decrease. This, in turn, lowers effective guardianship, an empirically supported protector against crime. Following the assumption of routine activity theory, reduced guardianship leads to increases in crime at those locations because people are not present both physically and socially.

Avoidance and Withdrawal

Now that I have reviewed the crime and place and routine activity theory literatures, I can briefly discuss behaviors that are often considered a consequence of assessed fear and risk at places. The majority of research that looks at behavioral change as a consequence of fear or risk indicates there are two primary behavior changes that occur when a person is fearful or feels they are at risk for victimization. These reactions are avoidance and defense.

Avoidance is the most often cited behavior and can include smaller changes like adjustments to travel patterns (Garofalo, 1981; Ferraro, 1995; Taylor, Gottfredson, & Brower, 1984; Doran & Lees, 2005; Rader, May, & Goodrum, 2007) to more severe forms like never leaving home or even moving out of an area (DuBow, McCabe, & Kaplan, 1979; Garofalo, 1981). Avoidance behaviors are thought to be socially distributed among certain population demographics like the elderly and women (DuBow, McCabe, & Kaplan, 1979; Garofalo, 1981). Moreover, some propose that populations can only engage in specific avoidance strategies because they may be limited by income or other problems of disadvantage (Garofalo, 1981).

The second most noted and supported behavioral changes in response to fear and risk are defensive behaviors. Defensive behaviors are those that people use to defend or prepare themselves against potential victimization. Good examples of these behaviors include carrying pepper spray or mace, carrying a gun, installing locks or extra lighting on their homes, etc. (DuBow, McCabe & Kaplan, 1979; Ferraro, 1995; Liska, et.al. 1987; Hale, 1996). Like avoidance, some people are limited in their ability to participate in defensive behaviors because of poverty or other issues related to disadvantagement (DuBow, McCabe, & Kaplan, 1979; Garofalo, 1981; Ferraro, 1995).

The literature tends to find strong empirical support for both avoidance and defensive behaviors by respondents who report being fearful or who report high anticipation of crime risk (DuBow, et.al., 1979; Liska, 1987; Ferraro, 1995). DuBow, et. al. (1979) cite that both limited behaviors and avoidance behaviors are strongly, positively associated with the fear of street crime, perceived risk of victimization, and with neighborhood crime rates. Interestingly, effects of avoidance and withdrawal, which are a result of fear, can ultimately lead to increases in fear and beliefs about risk, forming a cyclical relationship between fear of crime, risk assessments, and behavior (Liska, Sanchirico, & Reed, 1987).

The effects of fear and risk perception extend beyond individual behavioral changes. Many suggest that avoidance and defensive behaviors have consequential effects like community-wide non-involvement (Wilson & Kelling, 1982; Lewis & Salem, 1985; Skogan, 1986) and increased mistrust and suspicion among community members (Ross & Jang, 1996; Ross & Mirowsky, 1999). DuBow and colleagues (1979) note, "avoidance and protective behaviors may decrease social interaction and informal social control which in turn could reduce crime" (p. 35). Skogan (1986) notes increases in avoidance and withdrawal behaviors potentially affect the social fabric of the neighborhood causing decreases in trust and proactive responses to crime threats. As people withdrawal from the community and become suspicious of others, there is a decrease in informal social controls and collective efficacy (Skogan, 1986, 1990; Hale, 1996; Ross & Mirowsky, 1999). This decrease is considered to further contribute to escalating levels of fear of crime (Liska, et. al., 1987). Ultimately, avoidance and defensive strategies have a negative influence on the community and they appear to also contribute to escalating levels of fear, forming a problematic cycle.

Overall, this body of research supports the idea that behavior changes can affect the social climate within communities. Specifically, when people avoid certain places or withdrawal from a community, the community suffers because resident interactions are reduced thus negatively impacting informal social control and collective efficacy (Wilson & Kelling, 1982; Skogan, 1986; 1990). Strangely, the responsive behaviors to crime threats and fears actually have the potential to allow for further increases in crime because important functions, such as individual and collective guardianship are reduced.

Although it may be quick to assume that reported behavior is equivalent to actual behaviors, the literature does support that actual behaviors are conditioned by the way people read and respond to the environment around them (Ley, 1974; Gilmartin, 2000). Regardless of whether people are responding to actual crime, to their perceptions of crime, to their perceptions of risk and safety, or to overall fear, people often modify their behaviors as a way prevent possible victimization and unwanted situations.

Perceptions of Crime Locations

To date, only a handful of studies attempt to examine the places or areas where people believe crime is located. Overall, these studies tend to find that perceptions of crime locations to actual crime hot spot locations often have little to no correlation (Brantingham & Brantingham, 1977). Instead, what often happens is that other factors, separate from knowledge of crime, influence behaviors (Rengert & Pelfrey, 1995; Ratcliffe & McCullough, 2000; Matei, et.al, 2001). However, since there has been so little research that tries to examine this issue, other factors that can have an influence on whether people consider a place to be safe, risky, or high in crime have yet to be identified.

As an attempt to explain the underlying differences that result from cognitive mapping exercises of crime, Gilmartin (2000) cites five primary factors that can inform an individual's response. Existing studies have examined only a few of these factors. However, the closely related fear of crime literature has found all of these elements to be significant.

The first factor is actual crime – meaning respondents' perceptions of high crime areas are in fact the result of high levels of crime in them. A second possible influence on crime location identification is ecological labeling, or a person believing an area is high crime because they have received information, via media, friends, family, etc., that the area is high crime. This is similar to factors like vicarious information and victimization that is often tested in fear of crime research. A third possible influence includes environmental characteristics such as incivilities, disorder and design characteristics. As we will see below, these have been found to have an impact on cognitions of high crime places, and this is also a consistent predictor in fear of crime and risk assessment research. Another possible influence on crime location identification is a person's individual and psychological factors. Possible influencers are demographics and even cognitive feelings including feelings of powerlessness and vulnerability in an area, regardless of the crime levels there. Finally, Gilmartin (2000) cites that differences can be the result of the time of day (i.e., day perceptions versus night perceptions). Past research has also found this can cause significant differences in responses both in cognitive mapping of crime locations and in overall fear of crime research.

Furthermore, past research has been able to conclude there are certain environmental and communicative factors that can influence perceptions. Specifically, factors related to disorder (Rengert & Pelfrey, 1995; Doran & Lees, 2001), the built environment (Brantingham & Branthingham, 1997; Nasar & Fisher, 1993) and prioritization and communication (Matei, et. al., 2000; Ratcliffe & McCullough, 2001) have all been found to have an effect on the places that people mark as high crime. One area that has not yet been tested is how individual factors influence individual perceptions of crime places.

Overall, this study will take a first look at this issue and try to determine what individual based factors, like demographics and reported perceptions of crime and disorder, influence whether respondents can accurately identify a place as a crime hot or cool spot. Additionally, this study will also test the influence of actual crime (via tested accuracy) and time of day differences in perceptions. However, before we can get into the details of this study, it is important we review what has been done and what needs to be done in this line of research.

In one of the first studies that compared the areas people identified to actual crime locations, Brantingham & Brantingham (1977) essentially found that there were high levels of misperception of crime locations by respondents. In the study, the authors asked residents of an apartment complex to identify, on a paper map, where crime happens. Although crime often happened in areas central to the apartment complex, residents were more likely to name crime locations that were on the perimeter of the location, where the property bordered a wooded area. I should note this study was preliminary and was mostly diagnostic, so no explanation as to why there were substantial mismatches was given.

Rengert & Pelfry (1998) used a cognitive mapping approach to examine the differences between areas identified as safe between two groups: university students and police cadets. In the study the researchers asked respondents to rank, from highest to lowest, the areas on a map that were most dangerous and crime ridden in the city of Philadelphia. The study resulted in some interesting findings. Specifically, it was found that familiarity with key landmarks, like Philadelphia's city center, did not impact whether respondents considered that place to be safe. They also were able to determine that the areas respondents from both groups ranked as most dangerous in a city are in fact related to the presence of high minority populations and not actual crime. The authors argue the mismatches are the result of the difference between potential safety and actual safety, citing that areas of potential safety influenced perceptions more than actual safety (measured by levels of crime). Although this study examined group-level differences (i.e., cadets versus students), the study did not take into account other potential factors that might explain differences between respondents.

Matei and colleagues (2000) used cognitive mapping exercises to compare areas of comfort and safety to high crime areas. Their findings mimicked past research in that the areas identified as high crime were in fact not so. Instead, similar to the results of Rengert & Pelfrey's (1996) study, it was found that the one factor related to the areas marked was minority populations (specifically Black and Hispanic). Moreover, their research looked at the relative distance between a person's own neighborhood to those they marked as unsafe, and it was found that respondents considered their own neighborhoods to be secure, even if they were high crime. Instead, respondents more often identified areas away from their homes as unsafe and problematic.

Doran and Lees (2005) used a cognitive mapping approach to compare places of reported avoidance to actual crime and disorder in those same locations. They determined that although there was some overlap between actual crime and actual disorder, the areas that people avoided were not necessarily high crime. Additionally, the only overlap between areas that were collectively avoided was small and it was with instances of actual disorder, not of crime. This finding is interesting considering what the literature says about perceptions of disorder. Specifically, Gau and Pratt (2008) have found that respondents are not really able to distinguish the difference between physical and social disorder and that often times they cannot even distinguish a disorderly area from a high crime area. Thus, these findings imply, that areas that are perceived as unsafe may in fact be safe, and as the Brantinghams (1977) and Rengert and Pelfry (1998) suggest, misconceptions can lead to higher instances of victimization because of real yet unanticipated risks.

When examining differences in cognitive maps of crime, Nasar & Fisher (1993) made two interesting discoveries. First, they found that people's reports of danger/high crime areas were influenced by whether the location was low prospect, high concealment, and high in blocked escape. Essentially this means that respondents' reports of fear and risk increased with negative changes to the environment that would allow for the commission of a crime. Furthermore, in their study, they asked participants to identify how they react in the unsafe areas identified in the study. Overall, 96% reported that they made at least one behavioral change, with the most often change being avoidance (49%), followed by protective action (33%) and collective action (18%). Likewise, they found when they observed the areas that were identified as high risk in the mapping portion of the study, people engaged in changed behaviors, including avoidance (i.e., walking a different route) and collective action (i.e., walking in groups) while at these locations. This study's importance lies not only in that it was the first to explain differences in responses concerning crime locations, but it also goes one step further in that it makes a clear connection between perceived danger and actual behavior changes.

A final study using a cognitive mapping approach tested the accuracy with which criminal justice practitioners were able to identify crime locations within their jurisdiction (Ratcliffe & McCullough, 2001). The authors find that officers were able to accurately identify crime hot spot locations for one crime type – residential burglary – and were less successful in identifying crime hot spots of vehicle crime and non-residential burglary. Ratcliffe & McCullogh (2001) attribute this finding to the way that officers prioritize the different crime problems in their jurisdiction. Specifically, they note that residential burglary had been established as a priority crime problem by the community and by the department, therefore bringing it to the forefront of officers' attention. Since this crime problem was a priority, more so than auto theft or non-residential burglary, prior knowledge of this problem allowed them to better identify the problem places. Consequently, the authors determined that officers' perceptions of crime spots were directly affected by the communication and information they had received about those places.

Overall, research concerning the identification of crime locations has allowed us to understand not only the accuracy (or inaccuracy) with which residents or criminal justice practitioners perceive crime places, but also how these perceptions can potentially influence behavior, which can result in further crime. For instance, scholars suggest that because there is such a clear mismatch between perceptions of crime hot spots and actual crime hot spots, people may find themselves in situations that present an increased risk of victimization (Brantingham & Brantingham, 1977; Rengert & Pelfrey, 1998). For example, if a person does not recognize a crime hot spot, and instead perceives a place to be hot because of other environmental cues, such as disorder, residents will continue to travel to high crime areas without the knowledge that they are at a higher risk of being victimized. Likewise, by not traveling to areas that are otherwise not a crime problem, guardianship in these areas is decreased which potentially increases opportunities for crime in these areas, leading to unexpected increases at otherwise non-crime locations. Overall, the implications for explaining and understanding what influences perceptions of places are quite necessary because this knowledge can potentially provide better strategies for crime prevention and reduction.

Fear of Crime, Risk Assessments, and Safety

As the review above illustrates, research that examines perceptions of crime locations is limited and has yet to understand fully the factors that influence respondent accuracy at identifying crime places. Although a few of the studies uncovered relationships between physical and social disorder, there has not been a complete examination of how responses vary based on individual differences. When thinking about how to go about designing a comprehensive study, a natural starting point is the fear of crime literature. The fear of crime literature is an extensive body of work that has developed over the last 30 years. Studies in this genre have been exhaustive in their attempts to understand what demographic and environmental factors influence people's perceptions and fears of crime. Over time, the predictors and methodologies used in the fear of crime literature have evolved and have a strong degree of empirical support.

Likewise, the fear of crime literature has substantial links to risk assessment and avoidance and withdrawal behavior studies (DuBow, et al. 1979, Liska, 1987; Ferraro, 1995). The research illustrates that respondents who report being fearful or who have high anticipation of risk are more likely to engage in avoidance and withdrawal behaviors. This study seeks to advance this research by diagnosing and understanding which individual level factors influence the places that people avoid. Because of the linkages across these concepts, in some ways the methodology used here is just an alternative way for respondents to report concerns about safety and fear.

Consequently, what comes next is a review of literature related to individual demographic, perceptual, and neighborhood familiarity factors and their influence on a person's assessment of fear and risk. Before we start this section, it is relevant to note that although the two concepts of risk and fear have distinct differences in their definition and measurement, the concepts are very close and both provide a relevant research background to this study. Below is a review of fear as it relates to individuals, disorder, and residential tenure and familiarity, all of which will be included as independent variables in the present study.

Fear and Individual Demographics

Individual level factors are consistently included in fear of crime research. Results from fear of crime studies find individual level factors impact people's fear of crime (Franklin, et. al., 2008; McCrea, et. al., 2005). I should note, there is some debate as to whether fear of crime and risk assessments are better explained by individual demographics or environmental elements, such as physical and social disorder. Regardless of the debate concerning the strength of causality explained by individual level variables and about what exactly they predict, studies consistently agree that individual level factors matter to research regarding fear, risk, and safety.

For instance, several studies find that age significantly influences fear of crime (Warr, 1984; Liska, Sanchirico & Reed, 1987; McGarrell, Giacomazzi, & Thurman, 1997; Rader, May, & Goodrum, 2007). In the research that tests the age and fear of crime relationship, results regularly conclude older respondents are more fearful. These findings hold even when the dependent variable is changed to measures of risk (Franklin, Franklin, & Fearn, 2008). Interestingly, studies also find that the age and fear of crime relationship varies by crime type (Warr, 1984) and that the effect of age tapers off after the age of 70 (Liska, et. al., 1987). Some noted that continued escalating effects of age on the fear of crime are often the result of worry or risk perception (Kanan & Pruit, 2002). However, Kanan & Pruit (2002) argue their data "indicate that the age effect is more in line with ‘real’ victimization risk, as older individuals are less likely to report worrying about crime” (p. 543). Older respondents report they are more fearful because they believe they are more vulnerable to victimization (Liska, Sanchirico & Reed, 1987).

Gender is another individual level variable that influences fear of crime (Garofalo & Laub, 1978; Hale, 1996). Some suggest gender is the best predictor of the fear of crime (McCrea, Shyy, Western, & Stimson, 2005). Unlike other individual level factors, scholars consistently find gender to be significant across different dependent variable constructs of the fear of crime such as perceived risk, perceived safety, and avoidance behaviors (Kanan & Pruit, 2002). Fear of crime research finds that women are more fearful of crime than men, even when controlling for crime type (Harnagel, 1979; Warr, 1984; Ross, 1993). Women also have higher levels of perceived risk than men (Chiricos, McEntire, & Gertz, 2001) and are more likely to engage in avoidance behaviors (Rader, May, & Goodrum, 2007).

Several past studies also find that race is a significant predictor of fear of crime (Garofalo & Laub, 1978; Hartnagel, 1979). Like age and gender, the predictor effects of race are found in studies that use different measures of fear of crime, such as risk and safety (Chiricos, McEntire, & Gertz, 2001; Franklin, Franklin, & Fearn, 2008). Interestingly, several studies find that situational settings actually intensify the impact race has on the fear of crime. Covington & Taylor (1991) find that “those whose racial identity – whether black or white – diverges from neighborhood composition are more fearful” (p. 240). It is thought that the variation in the impact of race on the fear of crime intensifies when situations are more outside of the persons’ normal activities or environmental exposure (idea of dissonant context – see Covington and Taylor, 1991).

A person's income and/or social status can also negatively affect fear of crime levels (Hartnagel, 1979; Garofalo & Laub, 1978; Garofalo, 1981; Taylor & Hale, 1986). According to Taylor and Hale (1986), social class, is one of the strongest predictors to the fear of crime. Across the literature it is found that the lower a person's income the more fearful of crime they are likely to be (Hale, 1996). Like age, gender, and race, significant findings regarding income emerge even with variations in the operationalization and measurement of the fear of crime concept. Income and social class are found to have an effect on the fear of crime (Taylor & Hale, 1986; McGarrell, Giacomazzi, & Thurman, 1997) perceived risk (Chiricos, McEntire, & Gertz, 2001), safety assessments (Carvalho & Lewis, 2003) and avoidance behaviors (Rader, May, & Goodrum, 2007).

Similarly, a respondent's education can impact their assessment of risk and their fear of crime. Respondents that are more educated tend to be less fearful of crime (Hartnagel, 1979; Ross, 1993; Franklin, Franklin & Fearn, 2008; Rader, May, & Goodrum, 2007). Again, the effects of education are prevalent regardless of whether the study is testing fear of crime, risk of victimization (Franklin, Franklin, & Fearn, 2008) or avoidance behaviors (Rader, May, & Goodrum, 2007).

There are a number of other individual level factors that have been found to influence fear of crime levels but are not consistently tested in past research. For instance, prior victimization has been found to increase fear and risk perceptions among respondents (Skogan & Maxfield, 1981; Roundtree & Land, Chiricos, McEntire, & Gertz, 2001; Rader, May, & Goodrum, 2007). However, Skogan & Maxfield (1981) caution researchers on the use of previous victimization as a measure of the fear of crime. They note that even though those that have been a victim in the past are more fearful, only a small percentage of respondents are prior victims. This leads to issues with statistical power in fear of crime models (Skogan & Maxfield, 1981). Other influential factors on the fear of crime include access to second-hand information, such as the media or vicarious victimization of family, friends, or neighbors (Skogan & Maxfield, 1981; Hale, 1996; Koskela & Pain, 2000), poor health - mediated through walking (Ross, 1993), marital status (Ross, 1993), and negative opinions and low legitimacy of the criminal justice system (Rader, May, & Goodrum, 2007).

Overall, past research on individual demographics that affect individual fear of crime and risk assessments have found that age, gender, ethnicity, income/social status, and education have a significant effect on reported fear and risk assessments of surveyed individuals. Consequently, each of these individual demographic measures are included in this study to test whether they influence an individual's identification of an unsafe or dangerous location. Based on prior work, the expectation is that these factors will indeed have a significant impact.

Fear and Disorder

Disorder (or incivilities) is a concept often used to help explain both the existence of crime (Taylor & Hale, 1986; Taylor & Shumaker, 1990) and perceptions of crime (Skogan & Maxfield, 1981; Skogan, 1990; Wilson & Kelling, 1982). In fact, many studies identify disorder as the key explanatory variable in understanding individual reports of fear and risk assessments (Skogan & Maxfield, 1981; Rohe & Burby, 1988;

Wikstrom & Domen, 2001; Austin, Furr, & Spine, 2002; Robinson, Lawton, Taylor, & Perkins, 2003; Franklin, Franklin, & Fearn, 2008; Hinkle & Weisburd, 2008; Wyant, 2008). Overall, research tends to conclude that above all other measures, including individual demographics and the actual crime rate, disorder has the strongest influence on individual assessments of safety, risk, and fear.

Studies often identify two forms of disorder: physical and social. Physical disorder or incivilities often include "abandoned buildings, graffiti, litter, vacant and trash-filled lots, unkempt yards and housing exteriors, abandoned cars, and…the conversion of houses and apartments to drug selling locations (Taylor, 1999, p. 1). Taylor (1999) describes social disorder or incivilities to include things such as "public drinking and drunkenness, rowdy and unsupervised teen groups, sexual harassment on the street, arguing or fighting among neighbors, open prostitution, and…public drug sales and the presence of crack addicts" (p. 1). Scholars have found that both physical disorder and social disorder have a significant influence on assessments of fear (Covington & Taylor, 1991) and safety (Roundtree & Land, 1996; Austin, Furr, & Spine, 2002; Carvalho & Lewis, 2003). Although physical and social disorder are often identified and studied separately, some argue the two concepts are interrelated and there is no real statistical difference between them (Xu, Fiedler, & Flaming, 2005; Ross & Mirowksy, 1999). Regardless of whether disorder is measured as two concepts or one, it is consistently found to have a significant impact on fear and risk assessments of individuals.

A vast amount of research has been done to understand the connection between disorder and the fear of crime (Taylor, 1999; Maxfield, 1984; Ross & Jang, 2000; McGarrell, Giacomazzi, & Thurman, 1997; Covington & Taylor, 1991; Lewis & Maxfield, 1980). Findings suggest that both actual disorder (Covington & Taylor, 1991, more cites) and perceptions of disorder (Maxfield, 1984; McGarrell, Giacomazzi, & Thurman, 1997) have a significant influence on risk and fear assessments of people. Additionally, some causality has been established concerning disorder and fear. In a time sensitive analysis Robinson and colleagues (2003) find that disorder has a causal impact on neighborhood satisfaction, individual fear, and individual worry. Specifically, respondents who identified their neighborhoods as more problem-ridden were more likely to have feelings of dissatisfaction, worry, and vulnerability about their neighborhood the following year.

Interestingly, some find that the relationship between measures of disorder and assessments of fear and risk are mediated by other demographic and societal issues. McGarrell and colleagues (1997) found that demographic traits had a larger influence on reported fear levels for those living in low-disorder areas. For respondents who lived in high-disorder areas, the effects of other variables, such as age, ethnicity, and income were no longer significant. Instead, for high-disorder areas, they only found a direct link between disorder and fear levels. Similarly, Taylor and colleagues (1985) found significant effects for disorder and fear only in moderate income neighborhoods. Thus, it seems that although disorder can significantly influence fear on its own, there may be other societal and individual level conditions that can influence the relationship.

Although the disorder/fear of crime relationship is well studied and findings suggest that there is a clear relationship, there are some important criticisms worth noting. First, some argue that disorder and other concepts related to social control, such as collective efficacy, informal social control and crime overlap (Kubrin, 2008). Others note that often times individuals living in disorderly areas are also pre-disposed to other negative social conditions, such as low socio-economic status, and the effects of disorder and other phenomena on individual perceptions cannot be tested separately (Taylor, Shumaker & Gottfredson, 1985). Still, others suggest that those living in areas that are high in disorder are often desensitized to its overall effects and thus it may not communicate dangerousness and fear to the residents who live there (Taylor, 1999; Carvalho & Lewis, 2003).

Regardless of the criticisms mentioned above, research consistently finds that perceptions of disorder influence an individual's feelings of fear and assessments of risk and safety. Moreover, disorder is regularly identified as a primary influence on fear of crime. These conclusions point to the importance of including perceptions of disorder in any attempt at testing individual perceptions of crime and non-crime locations. Therefore, measures of disorder will also be included in analysis models discussed in Chapter Three.

Fear and Residential Stability and Neighborhood Familiarity

Although not often tested, fear of crime and risk assessment scholars often discuss the concepts of residential stability and neighborhood familiarity. Residential stability refers to residential tenure within a specified area. The concept of residential stability is often seen in literature regarding larger macro-level geographic studies (i.e., census block group, designated neighborhoods) and is regularly grouped within larger concepts such as concentrated disadvantage (Sampson & Raudenbush, 1999)

Research has mixed conclusions concerning residential stability and its direct relationship to fear, risk, and crime. Snell (2001) finds that residential stability is the strongest predictor of crime rates, but is not related to individual reports of fear. Yet, others find factors such as residing in an urban area (Liska, Sanchirico & Reed, 1987) and short residential tenure (Carvalho & Lewis, 2003) have a negative influence on the fear of crime.

More often, residential stability is considered to be an indirect link between disorder and crime (Skogan, 1990; Taylor, 1996; Sampson & Raudenbush, 1999). Skogan (1990) notes that many factors such as poverty and residential stability have a strong relationship with crime, but that relationship is only significant in models where disorder is also tested. Sampson & Raudenbush (1999) suggest, "If disorder operates in a cascading fashion – encouraging people to move (increasing residential stability) or discouraging efforts at building collective responses – it would indirectly have an effect on crime" (p. 637). The idea is that residential stability matters, but it may only matter in that it has a reciprocal relationship with disorder which can then impact individual perceptions and consequently crime.

Other research advocates that neighborhood stability has a significant influence on social cohesion and trust among neighbors. Thus, if stability in residential tenure of the neighborhood is low, there is less interaction among neighbors, reducing trust and increasing feelings of fear and vulnerability (Skogan, 1990; Taylor, 1996). Taylor (1996) explains,

> We find that neighborhood stability deepens residents' attachment to their locale and their involvement with neighbors. These community dynamics in turn influence resident's feelings of vulnerability, actions taken to reduce exposure to risk, and perceived willingness to intervene in disorderly events (Taylor, 1996, p. 70-1).

Interestingly, individual perceptions of trust and comfort potentially mediate the process that Taylor details. Specifically, trust and comfort are only possible when people know and interact with their neighbors – all of which is more likely when there is residential stability. Many argue a decrease in trust and social cohesion can lead to decreased collective efficacy and informal social control within neighborhoods (Sampson, Raudenbush, & Earls, 1997)

A concept relevant to this study but that is less often included in past research in neighborhood familiarity. The absence of this concept is rather interesting considering what research suggests regarding fear and place. Studies often conclude that residents perceive areas outside of their immediate surroundings (i.e., home territory) as more dangerous or unsafe, regardless of actual crime levels (Garofalo & Laub, 1978; Brantingham & Brantingham, 1993). Furthermore, some studies suggest that respondents with a higher level of familiarity are better at assessing safety (DuBow, et al, 1979; Siberman, 1981; Ferraro & LaGrange, 1987). Based on this logic, neighborhood familiarity might have a positive impact on assessments of places by those who live there. I contend that neighborhood familiarity is an important concept to test because we would assume that those who live in high crime areas will have the best knowledge of areas that are risky and can more accurately report the areas they would avoid in an attempt to manage that risk.

Although not frequently tested, neighborhood familiarity and tenure are important constructs to include in studies that examine perceptions about very specific micro-level geographies such as street segments. It is important to include them because a good portion of reports of unsafe or dangerous areas might be explained by a person's nuanced knowledge of an area. If a person has lived in the area for a long time or if a person is more familiar with an area, they might have better knowledge of specific locations that contain dangers that could lead to victimization. Consequently, these measures are included in this research.

Conclusion

From the review contained in this chapter, we know that many factors can explain a large amount of variance in an individual's fear of crime, assessment of risk, and reported locations of crime. Specifically factors related to individual demographics (e.g., age, gender, ethnicity, education, etc.), perceptions of disorder (e.g., physical and social disorder) and neighborhood familiarity and tenure all seem to have an influence on perceptions of fear and safety. Based on the review of past location-based crime perception studies, some of these concepts, including disorder and familiarity, can also influence the locations that people believe to be crime ridden, often times more so than actual crime.

This study is relevant to the larger realm of criminology because its main purpose is to identify how accurate people are at identifying areas containing the most risk, and what factors, if any, inform these assessments. By understanding what individual level factors influence perceptions, research can begin to explain specific behaviors, such as avoidance and withdrawal, within particular locations. Additionally, this study has the potential to lead to preliminary explanations of why crime concentrates at places through the mechanism of guardianship.

CHAPTER 3: RESEARCH QUESTION & STUDY DESIGN

In this chapter, I present the study's research questions along with the research model and subsequent hypotheses. However, before moving forward, it is necessary to first discuss the limitations of past crime location perception research. Doing so will help justify the methodology used here. Furthermore, it will illustrate the utility of the study questions.

Limitations of Past Research

Only a few studies have tried to examine cognitive perceptions of dangerous or crime places and how they relate to crime hot spots (Ley, 1974; Brantingham & Brantingham, 1977; Nasar & Fisher, 1995; Rengert & Pelfry, 1997; Doran & Lees, 2005). Although each of these studies contributes to understanding how people perceive the geography of crime and fear, there are some limitations with the methodologies and analytic strategies used. For instance, the majority of past studies (excluding one – Nasar & Fisher, 1995) examine perceptions of place for macro-level geographies. Often, studies require respondents to give their opinions about larger geographic areas such as a census block group or even a politically designated neighborhood. The problem with this is that much of the research on the geography of human behavior and of crime indicates that real "neighborhood" environments tend to exist at the street block level (Taylor, Gottfredson, & Brower, 1984; Weisburd, et al., forthcoming). Additionally, Nasar & Fisher (1993) find,

> Different processes underlie responses to hot spots at different scales. For large areas, such as a country, city, or neighborhood, individuals cannot apprehend the whole place at once. They develop mental images of hot spots of fear without necessarily having a direct environmental experience. Indirect experience such as media report, rumors, and recalled past experience may affect the image (p. 188).

Overall, past studies do not do a good job of translating perceptions as they relate to very specific places such as a street block. This is problematic given research that suggests people perceive and recall places at a very micro level.

Second, past studies on perceptions of geographies tend to force people to make assumptions about pre-defined areas. For instance, many studies, even those that use cognitive mapping methods, often ask people to rate their feelings of safety, fear, or assessments about crime and victimization as it relates to a pre-defined location like a census block group (Rengert & Pelfry, 1997; Matei, et.al, 2000). Rarely do these studies let individuals pick apart these areas and explain the dynamics occurring inside of them. This is problematic because it limits the ability of the research to assess the variability in fear and risk responses at the micro-level.

A third problem with past research concerning cognitive maps of crime hot spots is that it fails to account for individual differences that might influence people's perceptions. According to Brantingham & Brantingham (1984) these group differences exist - even when looking at perceptions of risky areas and crime locations. Ideally, following findings from other disciplines such as geography and social psychology, these factors should make a difference in the way people perceive and interpret places.

The overall goal of the present study is to further research on environmental perceptions and consequential behaviors by addressing some of these limitations. Specifically, in this study, areas considered unsafe or dangerous were collected using cognitive maps, and were then compared to micro locations of crime. This approach reduced past limitations in that the maps did not limit responses to larger level macro areas. Essentially respondents could mark as much of the map as they deemed appropriate when reporting the areas where they feel unsafe. Furthermore, this approach was used so that respondents had the ability to pick apart a larger 'neighborhood' with the hopes of understanding and addressing the different individual level factors that account for variations in responses.

Before moving further into the study questions and hypotheses, I should clarify that in this study, a place is approximately the size of a city street block (i.e., a street segment from intersection to intersection). This definition of place is in line with definitions and standards used in crime and place research (Sherman, et al., 1989; Sherman & Weisburd, 1995; Weisburd & Green, 1995; Weisburd, et. al., 2004). Moreover, recent theories about actions at places suggest that behavior-settings, or "…the part of the environment which an individual, at a particular moment in time, can access with his or her senses, including any media present" influence individual behaviors (Wikström, 2006; Oberwittler & Wikström, 2009, p. 36). Thus, because an individual can only interact with a very small geography at a given time, a behavior setting refers to a very small, micro-location. Since we know that hot spots and behavioral setting environments occur at these very specific geographies, the street block segment is the most appropriate when determining reasons why people identify places as they unsafe or dangerous.

Additionally, I should clarify the definition of the terms hot and cool crime spot. Traditionally, a hot spot is defined as a specific location, often no larger than a city street block, that houses high levels of crime (Sherman, Gartin, & Buerger, 1989; Sherman & Weisburd, 1995; Weisburd, & Green, 1995; Weisburd, et al., 2004). Conversely, a crime cool spot is a street segment that has no crime or has relatively low levels of minor offenses over time. Because research has shown us that crime hot spots tend to be sparse and variable throughout larger geographies (i.e., census tract, city, etc.), the presence of crime cool spots is expected to be abundant and clustered. Therefore, for this study, I also use a sample of crime cool spots within the designated area for analysis. A detailed discussion of this process is included in Chapter Five.

Research Questions and Hypotheses

The present study seeks to address two important questions. The first question asks, "How accurate are respondents at identifying crime hot spots in the areas they consider to be unsafe?" Additionally, the second question asks, "How do different individual demographics and perceptual factors influence the accurate identification of crime hot spots?" For each of these larger questions, I have derived a number of key hypotheses to test. I detail each of the questions and hypotheses below.

Question 1: Respondent Accuracy

The first goal of this study is to understand how accurate respondents are at including crime hot spots, and subsequently not including crime cool spots, in their perceptions of unsafe places. Again, this study's importance lies in how these perceptions influence behaviors, therefore affecting the context and dynamics of places. From the tenets of routine activities theory, we would expect that locations where people are less likely to frequent would harbor a majority of crime because they go unguarded. The fundamental assumption behind this supposition is that people know and avoid actual crime locations.

Although the research indicates that respondents are not accurate in their identification of crime locations, past studies have been limited in their approach. Therefore, the first hypothesis predicts that respondents will be accurate in their identification of crime locations. Conversely, if respondents are accurate in their inclusion of crime hot spots, I predict that they will also be accurate in the identification of crime cool spots by not including the randomly selected crime cool spots in the areas they deem as unsafe or dangerous.

- *Hypothesis 1: Respondents will accurately identify general and violent crime hot spots in the areas they consider to be unsafe or dangerous.*
- *Hypothesis 2: Respondents will accurately identify crime cool spots in the areas they consider to be safe.*

In the literature there is much criticism over the use of the word "crime" when measuring fear of crime and assessments of risk (Ferraro & LaGrange, 1987). Specifically, past work indicates that the use of general crime is too broad when trying to understand fear and risk assessments (Garofalo & Laub, 1981). Moreover, research concludes that fear of crime and risk assessments often have stronger links to violent personal crimes (e.g., assault, robbery, rape, etc.). Therefore, in this study, I will examine if accuracy of hot spot identification improves when using only violent crime hot spots. From the literature, I predict that respondent hot spot accuracy will improve.

- *Hypothesis 3: Respondents will have increased accuracy scores when identifying violent crime hot spots compared to scores of general crime hot spots*.

Lastly, past literature in both cognitive mapping and fear of crime, the understanding is that perceptions change with the time of day dynamic (Skogan & Maxfield, 1981). Based on findings in past research, it is reasonable to assume here that respondents will draw different locations for their reports of the different phenomenon. Thus, the following hypothesis will be tested:

- *Hypothesis 4: The accuracy of hot spot identification by respondents will improve from day to night.*

- *Hypothesis 5: Respondents will be less accurate at cool spot identification from day to night.*

Overall, the first goal of this study is to assess how accurate respondents are at including crime hot spots in the areas that they deem unsafe. Furthermore, it examines how well respondents identify crime cool spots in areas that they consider to be safe. From this simple goal, additional questions emerge. Furthermore, how if at all, do accuracies of respondents differ from based on the time of crime and time of day? This study addresses each of these questions.

Question 2: Predictors of Respondent Accuracy

The second goal of this study is to determine what individual level factors account for variations among respondents in accuracy scores. Much of the literature suggests a number of individual demographic factors significantly influence individual fear of crime and assessments of risk and safety. For a full review of the different factors, see the extensive literature review in Chapter Two.

The literature suggests that the most commonly tested are factors such as age, gender, and race/ethnicity. Other demographic factors such as income, education, and marital status can also influence individual assessments of fear and safety. Consequently, I hypothesize that age, gender, ethnicity, education and marital status will all have a significant impact on a person's identification of a designated place as hot or cool with crime. Statements concerning these anticipated relationships are listed below:

- *Hypothesis 6: Older respondents will be less likely to accurately predict micro-level crime hot and cool spots.*

- *Hypothesis 7: Female survey participants will be less able to predict hot and cool crime spots as male respondents.*

- *Hypothesis 8: Ethnic/racial majorities will be better able to predict micro-level crime hot and cool spots.*

- *Hypothesis 9: Respondents who are more educated will be better able to specifically predict crime hot and cool spots within the neighborhood.*

- *Hypothesis 10: Single respondents will be less likely to accurately predict micro-level crime hot and cool spots within the neighborhood*

In addition to the many demographic factors, research suggests that there is a strong relationship between negative perceptions of disorder and crime on individual fear and assessments of safety. Likewise, research also suggests that perceptions of physical and social disorder dictate avoidance and withdrawal behaviors among people. Therefore, this analysis will examine how the factors of individual perceptions of physical disorder, social disorder and crime impact how well an individual identifies hot and cool crime spots within the larger neighborhood. In line with past research, it is presumed that individuals with more negative perceptions of physical and social disorder and of crime will have less positive perceptions of place. Below are four separate hypotheses concerning perceptions of disorder and crime and its anticipated effect on the places that respondent's mark as hot or cool spots of crime.

- *Hypothesis 11: Those who perceive higher levels of physical disorder in the neighborhood will be less accurate in their prediction of crime hot and cool spots in the neighborhood.*

- *Hypothesis 12: Respondents who perceive more social disorder in the neighborhood will have less accurate perceptions of the locations of hot and cool crime spots.*

- *Hypothesis 13: Those that report higher levels of neighborhood crime, will be less likely to accurately identify locations that have high concentrations of crime and those locations that do not.*

Research often finds that although people may live in crime-ridden areas, they do not feel their homes to be unsafe or dangerous. Instead, they often report areas outside of their "activity space" as potentially harmful (Brantingham & Brantingham, 1993). Thus, it is relevant to test what effects, if any, neighborhood familiarity and tenure have on a person's accuracy in identifying crime hot and cool spots. Here I will test the effect of five specific measures: time lived in the area, time lived in current residence, neighborhood familiarity, time spent outside of the home, and distance to the center of the place. Overall, I hypothesize that residents who have lived in the area for less time, those who have less familiarity with key landmarks in the neighborhood, those who spend less time outside of their home, and those who live further away from the place, are more accurate in their identification of crime hot and cool spots within their respective neighborhood.

- *Hypothesis 14: Respondents who are more familiar with the neighborhood will more accurately identify hot and cool spots.*

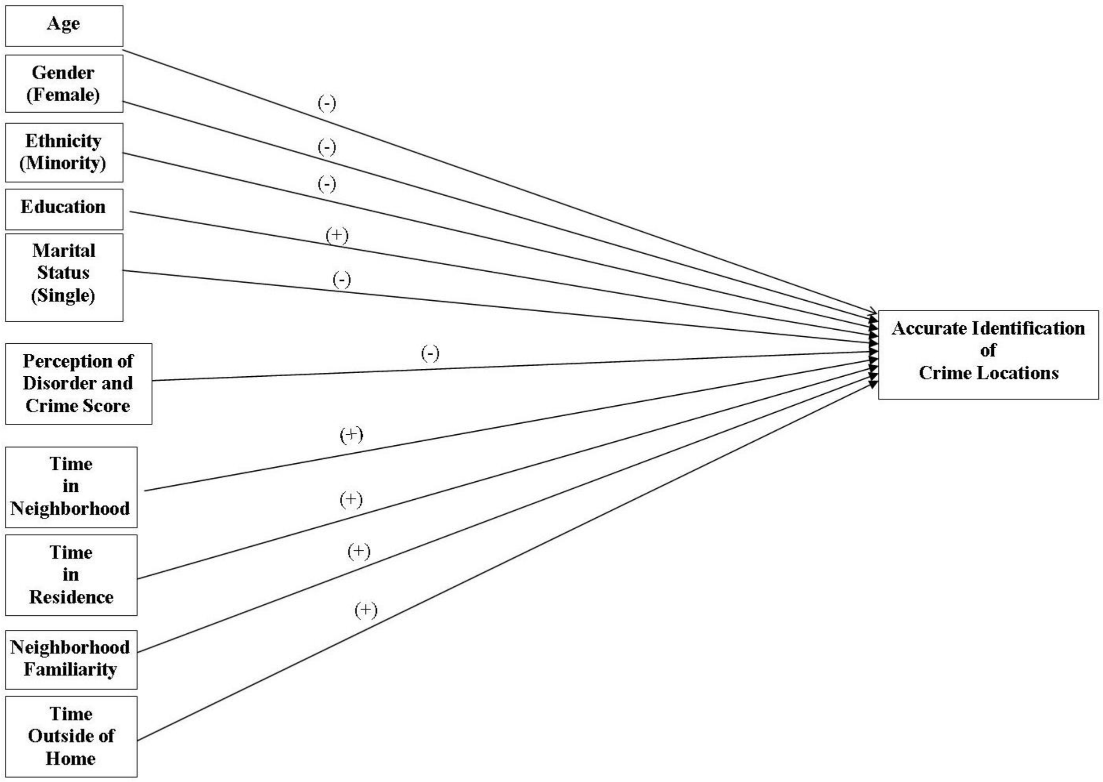
- *Hypothesis 15: Respondents who have lived in the neighborhood longer will be better able to predict where hot and cool crime spots are located.*

- *Hypothesis 16: Survey participants who spend more time outside of their home per week will be better able to predict crime hot and cool spots.*

Figure 3.1 proposes a path model for assessing the which predictors affect the accuracy with which respondents include crime hot spots in the areas they consider to be unsafe. This path model illustrates relationships between individual demographics, individual perceptions of disorder and community problems, and residential tenure and familiarity. It is assumed that each of the independent measures has a direct influence on the accurate identification of unsafe places.

Because there are so many variables, when possible, scored measures will be calculated in an attempt to reduce the amount independent variables in the model. A detailed description of how these variables are defined and combined is included in Chapter Five.

Figure 3.1 –Effect of Individual Demographics and Familiarity on the Accurate Identification of Unsafe Places



Overall, the model suggests that individuals who are older, single, female, minority, less educated, less familiar with the neighborhood, and who have lived in the neighborhood for a shorter amount of time will be less accurate in their identification of crime locations. Additionally, the model illustrates a direct relationship between perceptions of disorder and crime and a person's ability to accurately identify places high and low in crime – essentially it is hypothesized that those who have more negative perceptions of crime and disorder will be less likely to accurately identify hot and cold crime places in the community.

Conclusion

To conclude, this study will test sixteen hypotheses concerning both respondent accuracy and the impact individual predictors on the ability of respondents to identify crime hot and cool spots in their assessment of unsafe locations. First, I will examine how well respondents identify crime and non-crime locations, accounting for variations in both the crime type and the time of day. Furthermore, I examine how a number of variables concerning individual demographics, individual perceptions of disorder and crime, and individual factors related to neighborhood familiarity and tenure influence the identification of crime hot and cool locations.

The next chapter, Chapter Four, provides details concerning the survey and the crime data sources for this study. Specifically, I will review the selection and administration of the survey, which is the primary data source. I will also review the layout and structure of that the survey instrument. In addition to the survey, calls for service data are used to identify crime hot and cool spots in the areas of study, which are later used to help construct the dependent measures of accuracy.

CHAPTER 4: SITE SELECTION AND DATA

The present study will use data from the Community Problems and Issues Survey (CPIS), and the E-999 calls for police service data for the two study communities. The data were collected as part of a crime reduction initiative implemented by the Trinidad and Tobago Ministry of National Security known as the Trinidad and Tobago Police Service Project (TTPSP). The TTPSP was a two-pronged project to address the escalating violent crime problem in Trinidad and Tobago. The first portion of the project dealt with police reform and spear-headed initiatives related to improve training and promotion standards within the Trinidad and Tobago Police Service. The second prong of the TTPSP was tasked with addressing the severe crime problems in Trinidad and Tobago by implementing various evidence-based initiatives to combat crime. The CPIS was administered by researchers working on the crime reduction initiative as part of a larger gang violence and communities project. The crime data was collected from the E-999 Communications Centre under the Trinidad and Tobago Ministry of National Security.

Site Selection and Community Demographics

Trinidad and Tobago is a two-island nation located approximately 8 miles off the coast of Venezuela. Trinidad and Tobago is a relatively new democracy, having gained independence from Britain in 1962 (CIA Factbook, September, 2008). The islands are small in size; the surface area of Trinidad and Tobago combined is 5,128 square kilometers or approximately 1,980 square miles. To put the size of the islands into perspective, together the islands are roughly the size of the State of Delaware (1,982 square miles) (State of Delaware, 2008).

Based on the 2000 Census, Trinidad and Tobago has a population of 1,262,366 people. Of the approximate 1.26 million residents, approximately 96% are residents of Trinidad and 4% live in Tobago. The mean age of residents in Trinidad and Tobago is 30.54 years and the mean reported monthly income is $1,497.74TT (approximately $249.62 US). Females constitute a slight majority of the population (50.1%). The majority of Trinidad and Tobago residents identify themselves as Indian (40.0%).

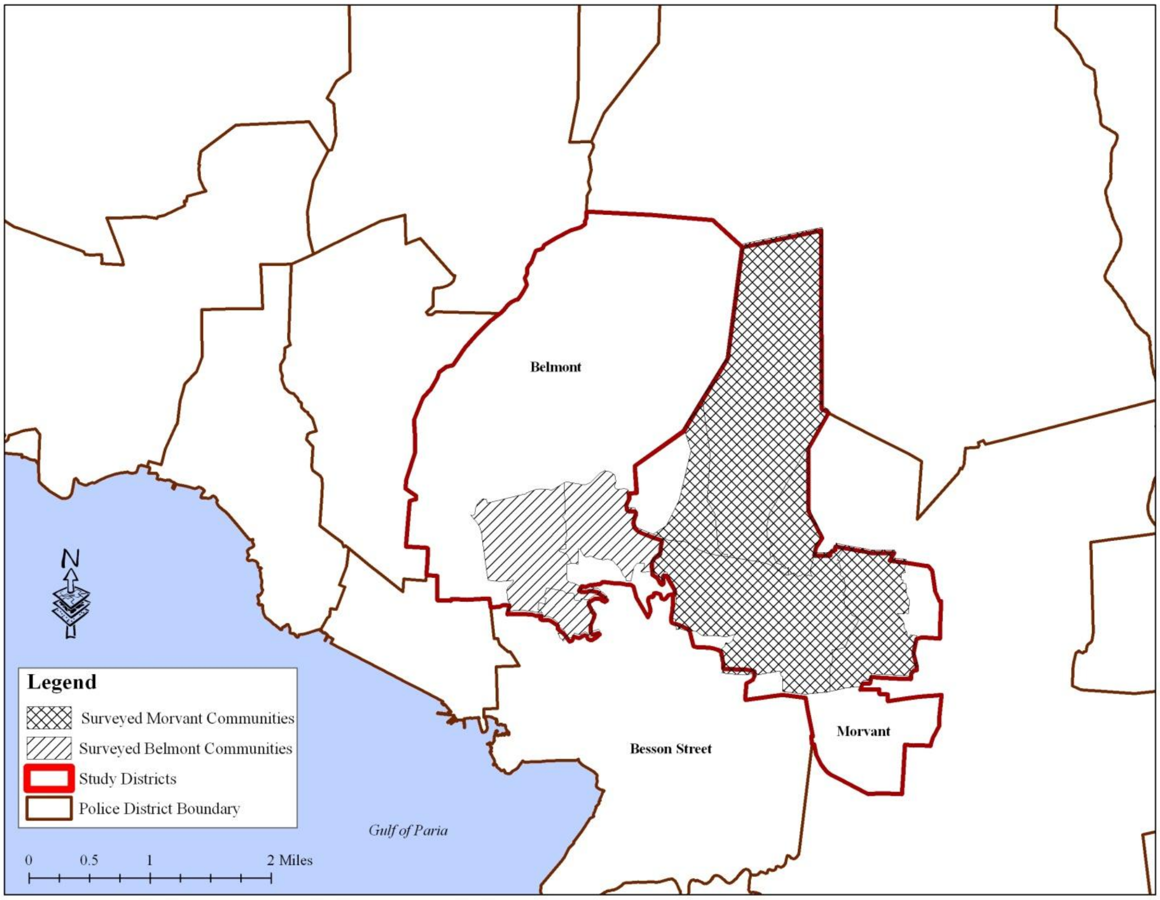
A large majority of Trinidad and Tobago residents (83.1%) report their highest level of education as primary (40.1%) or secondary (43.0%). Only 3.4% of the population report attending a University and 1.9% of respondents report they have never attended school. In the 2000 Trinidad and Tobago Census, 49.3% of respondents reported they were employed and working and 43.7% of respondents stated they have not looked for work (though it is worth noting that a large number of responses [25.6%] regarding economic activity were missing). The majority of Trinidad and Tobago residents (57.6%) stated they were of Christian faith, 22.5% of residents reported they were Hindu, 5.7% claimed they were Islamic, and 10.8% stated they were other.

Since 2000 Trinidad and Tobago has seen a substantial increase in violent crime rates. For example, homicides have increased from 98 cases in 1999 to 395 in 2007.[1] In particular, gun-related homicides were the fastest rising violent crime with a 959% increase over the eight year period between 1999 and 2007 (Maguire, et.al., 2008). Research has found that the rise in violent crimes, and specifically homicide, is mostly the result of gangs and street violence (Maguire & Katz, forthcoming). Additionally, the violence in Trinidad, and more specifically homicide violence, has been found to be confined to certain areas within the small country. Specifically, 7 of these police station districts, of 62, are responsible for over 50% of the nation's homicides (Maguire, et.al, 2008). Moreover, within these seven police station districts, there are specific concentrations of homicides over smaller geographies (Maguire, et.al, 2008).

Figure 4.1 shows the Belmont and Morvant station district areas. Additionally, the map in Figure 4.1 indicates the areas targeted for survey administration. These survey areas are identified by the shading within the Belmont and Morvant station districts. Please note that not all of the areas within the station districts were sampled. Instead, the survey was designed to only question respondents who live in areas that are affected by higher rates of violent crime and disorder.

[1] Homicides are used to display the crime trend because the homicide data is the most accurate and consistent of available crime data. Data obtained through TTPSP project from Trinidad and Tobago Police Service records.

Figure 4.1 – Surveyed Communities in Belmont and Morvant



The Belmont and Morvant station districts were selected as the survey sites for several reasons. First, both Belmont and Morvant fell within the top 7 high homicide station districts. From 2001 to 2007, 8.9% of all homicides occurred in Morvant (2nd place) and 4.6% occurred in Belmont (5th place). The Belmont and Morvant districts are also adjacent to Besson Street, the top ranked district for homicide (contains over 20% of all homicides). Figure 4.1 illustrates the proximity of the Belmont, Morvant and Besson Street districts.

The second reason these areas were selected is because the residents within them have reported victimization and fear concerning street violence and gang activity (Johnson, 2007). In the same survey, these respondents reported high instances of physical and social disorder in their neighborhoods, and reported lower legitimacy regarding law enforcement activities in their communities (Johnson, 2007). It was important to survey communities that had substantial problems with crime and disorder because researchers wanted to ensure that the survey was given to people they believed had to rely on spatial maneuvering and self-protection behaviors as a means of decreasing their victimization risk.

Figures from the 2000 Trinidad and Tobago Census indicate there are 22,624 people residing in Belmont. Approximately 52.7% of Belmont residents are female and 47.3% are male. The mean age for Belmont residents is 33.07 years and the average monthly income is $1,432.76TT ($238.79USD). Belmont residents are primarily African (64.1%) or Mixed (26.2%) and report their highest level of education is Secondary schooling (48.8%). A large percentage of Belmont residents (79.2%) report they are Christian.

The Morvant communities of interest have an estimated population of 28,437. The average age and income for Morvant residents is lower than that of the national average and of Belmont residents. Specifically, the mean age of Morvant residents is 29.84 years and the average monthly income is $1,172.99TT ($195.50USD). According to the census figures, Morvant residents are 51.3% female and 48.7% male. Morvant residents are predominately Afro-Trinidadian (72.9%). Similar to the nation as a whole and Belmont residents, the majority of Morvant community members report secondary schooling as their highest level of education (42.2%). Similar to Belmont residents, a large percent of Morvant residents also reported they were of a Christian faith (73.4%). Table 4.1 compares the demographic of the country as a whole to the selected districts of interest.

Table 4.1 – Demographics of Trinidad and Tobago, Belmont, and Morvant

	Trinidad & Tobago	**Surveyed Belmont District**	**Surveyed Morvant District**
Population	1,262,366	22,624	28,624
Population Density	ADD	ADD	ADD
Mean Age	30.54 years	33.07 years	29.84 years
Mean Income	$1529.64TT ($254.94 USD)	$1432.76 TT ($238.79 USD)	$1172.99 TT ($195.50 USD)
Gender			
% Male	49.9%	47.3%	48.7%
% Female	50.1	52.7	51.3
Ethnicity			
% Afro-Trinidadian	37.5	64.1	72.9
% East Indian	40.0	7.4	9.1
% Mixed	20.5	26.2	16.8
% Other	1.2	1.2	0.4
Education			
% Less than Primary	4.4	3.1	4.1
% Primary	43.1	38.1	45.8
% Secondary	46.2	52.9	46.0
% University	3.7	3.4	1.7
% Other	2.4	2.4	2.3
Religion			
% Christian	57.6	79.2	73.4
% Hindu	22.5	2.4	4.7
% Islamic	5.8	1.8	2.1
% Other	10.8	11.4	14.1
% None	1.9	3.1	3.5

In Table 4.1 we see that although residents of Belmont and Morvant seem to have similar age and gender distributions to all of Trinidad and Tobago, there are some interesting differences. Specifically, residents of Belmont and Morvant have higher percentages of Afro-Trinidadian populations, have a lower reported income, and they more often report being of Christian faith. Regarding education, residents from Belmont are similar to those from the rest of Trinidad and Tobago in that around 3.5% report graduating from a University. Morvant, however, is lower (1.7%). I should note that many parts of Belmont, especially those in the northern section, report being of upper-middle class to upper class. Thus, the income and education statistics might be affected from the aggregation of these measures at the community level.

Community Problems and Issues Survey (CPIS)

The primary data source for the present study is the 2008 Community Problems and Issues Survey. Respondents of the survey were recruited by a reputable Trinidad and Tobago research and marketing firm, using a snowball sampling methodology. To obtain the sample, representatives from the research firm contacted different community organizations in the two communities, including youth diversion programs, community watch programs, and churches, to see if they could approach potential participants of these organizations to invite them to participate.

Meetings were held with each of the different organizations so that the survey firm could introduce the study to the different populations. Representatives from the research firm gave contact information to the respondents to schedule an interview if there were interested in participating. All interviewers were scheduled to occur at the research firm office, which served as a neutral and safe location for respondents. In many instances, the research firm also provided transportation to those interested in participating.

Interviewers arranged appointments from interested parties until the sampling quotas for each neighborhood were reached (90 for Belmont and 90 for Morvant for a target sample of 180). The final sample consisted of approximately 168 of the targeted 180 active community residents. The full quota (90 respondents) was reached for Belmont. Although interviewers successfully recruited 90 respondents for Morvant, there were only 78 actual participants. This was due to two reasons. The first is that in some cases, representatives from the research firm were chased out of a Morvant neighborhood by gang members when they went to transport willing participants. Second, Morvant surveys were administered approximately two weeks after the survey start date, giving some participants time to become reluctant to participate after they found out about the content of the survey. Although the sampling was not done using a randomized design, the snowball sampling methodology allowed researchers to reach participants who were more active in the community overall. Table 4.2 represents the demographics of the survey participants by community.

Table 4.2- Respondent Demographics

	Belmont (n=90)	Morvant (n=78)
% of Respondents	53.6%	46.4%
Mean Age	32.53 years	31.94 years
Gender		
% Male	73.3	65.4
% Female	26.7	34.6
Ethnicity		
% Afro-Trinidadian	61.1	78.2
% Indo-Trinidadian	8.9	10.3
% Mixed	30.0	11.5
Education		
% None	0.0	1.3
% Primary	11.1	19.2
% Junior Secondary	7.8	2.6
% Secondary	60.0	60.3
% Vocational/Technical	11.1	12.8
% Tertiary	10.0	3.8
Marital Status		
% Single, Never Married	56.7	53.8
% Living with Someone, Never Married	22.2	21.8
% Married	11.1	15.4
% Separated/Divorced	6.7	3.8
% Widowed	3.3	5.1

Based on the information in the table we can conclude that the sample populations appear very similar. Both samples have a mean age of approximately 32 years. Likewise, the education levels of respondents are very similar, regardless of where they live. Interestingly, the biggest difference between the two sampled areas is that Belmont residents more often reported being of mixed ethnicity; however, both sets of respondents were primarily Afro-Trinidadian.

Although the main goal of the instrument was not to measure the prevalence of community issues and problems in the community where they lived or worked, the survey was carefully constructed so that the issues of dangerous places, crime, and gang territories could be approached in a manner that was non-threatening to respondents. During the development of the survey there was concern that respondents would not be comfortable participating in the survey if it only included questions that focused on crimes and gang activity. Thus, the survey was extensively pre-tested with both recruited community residents and police officers prior to the final survey administration. Changes were made so that the content was appropriate for the sample.

Survey Administration

Surveys were administered by interviewers from a local research firm in an undisclosed location outside of the communities under study. Respondents were offered transportation to and from the undisclosed location by recruiters. The community survey was not administered in the field for two specific reasons. First, because the instrument contained questions that relied heavily on respondents' cognitive processes, we had to ensure that there was a controlled, quiet, and comfortable setting for the instrument administration. Second, because the survey asked about sensitive topics such as crime and gangs, participants were taken to a neutral location outside of the community, so that both the community respondents and the interviewers could safely engage in the survey.

Each of the resident respondents participated in a one-on-one interview with an experienced interviewer in a private office. All respondents were 18 years of age, or older, and were allowed to refuse to answer questions or terminate the survey at any point in time. As promised in the recruitment sessions, respondents were paid $100 TT (approximately $16 USD) after completing the survey. Community surveys were administered over a period of two weeks in February, 2008. All community surveys were audio-taped with permission from the respondent, in order to accurately capture responses to open-ended questions. If a respondent refused to be audio-taped, they were still given the survey and interviewers were asked to make clear notes regarding the open-ended questions. A total of 118 respondents, or approximately 70.2% of respondents, agreed to be audio-taped during the course of the interview.

Survey Instrument

The Community Problems and Issues Survey was given to respondents in two parts. The first part was a standard survey questionnaire that focused on potential problems and issues within the communities. The second part of the survey consisted of a cognitive mapping exercise to measure respondents' perceptions about the dangerous areas and gang territories within their communities. Both approaches are discussed in further detail below. I should note that when respondents were surveyed, they were only asked to answer questions that related to the community where they live or work. Thus, participants were not asked to speculate as to the problems and issues in areas where they might not be as familiar.

Questionnaire

The questions on the Community Problems and Issues survey touched a variety of topics including a respondent's neighborhood familiarity, residential tenure, perception of social and physical disorder, general fear, and their individual demographics. The survey was designed so that respondents could answer questions regarding some of these issues without requiring them to put themselves in potential harm by disclosing information about particular crimes or criminal offenders. The survey is included in Appendix A of this study.

Individual Demographics

Respondents were asked a number of questions that addressed their individual demographics. Specifically, respondents were asked about the general location of their residence, their age, ethnicity, education levels, marital status, and family status. These questions were given to respondents for two reasons. First, these questions allow us to gain a sense of the sample demographic. Second, many of these questions including respondent age, gender, ethnicity, and education levels are important independent variables in the fear of crime and risk assessment literature.

Disorder and Neighborhood Problems

Disorder and Neighborhood Problems were measured through a number of questions related to disorder, crime, and gangs. First, respondents were asked how big of a problem disorder related issues such as trash, graffiti, vacant buildings, poor lighting, and empty and overgrown lots were in the community. They were able to reply a big problem, somewhat of a problem, not a problem, and do not know. Indicators of social disorder were captured with similar problem gauging questions that asked about groups of unsupervised teens, people buying and selling drugs on the street, drunk people in public, people smoking marijuana in public, loud or unruly neighbors, the presence of vagrants or homeless people, and youth truancy.

Gangs and gang activity have also been cited as considerable problems within Trinidadian communities (Johnson, 2007). Thus, the survey used measures to gauge whether gangs exist in the community and if so, their prevalence in the community. Specifically, respondents were first given a yes/no question asking if gangs exist. If respondents replied yes, they were then asked to estimate how many gangs they believed existed within their community. Lastly, respondents were asked whether they felt gangs were helpful, a problem, or necessary to their community.

Research suggests that residents of areas plagued with crime and violence tend to perceive dangerous areas differently than those living outside of crime-ridden areas (Garofalo, 1981). Thus, the survey included questions asking about the respondent's level of fear in particular situations. Specifically, respondents were asked if they would be very fearful, somewhat fearful, or not fearful in nine situations. Examples of the situations inquired about included if a stranger stopped them in their neighborhood to ask for directions, if they were walking alone in their community during the night, if they were walking with company at night, and if they were answering a knock at their door after dark. Scenarios were limited to those occurring within the community in an attempt to focus respondents to refer to areas that resonated more with their community and not foreign, far-away locations.

Neighborhood Familiarity and Tenure

Research has found that cognitions of space can depend heavily on a person's first-hand knowledge and experience within a space (Lynch, 1969; Lloyd, 1997; Kitchen & Blades, 2002). In an attempt to gauge the spatial knowledge of the respondents, participants were asked about their familiarity of major landmarks in their district. The survey utilized public community landmarks such as hospitals, churches, and schools as well as private-owned landmarks such as car dealerships and a mall. Respondents were asked if they were very familiar, somewhat familiar, somewhat unfamiliar or not familiar with the selected locations. A second question used to gauge neighborhood familiarity asked respondents about the average amount of time spent outside the home. This was done based on the assumption that if respondents spend more time outside of the home, they are going to be more familiar with their physical and social community.

Additionally, the survey used two questions to gauge a respondent's residential tenure within the community. First, they were asked how long they have lived in their community. Next, they were asked how long they have resided at their current address. This issue was addressed with two questions simply because the possibility exists that respondents could have moved during the course of their life, but may have stayed within the same community. This was done in order to capture the exposure time of each resident.

Cognitive Mapping Exercise

According to Kitchen & Blades (2002), "Cognitive map is a term that refers to an individual's knowledge of spatial and environmental relations, and the cognitive processes associated with the encoding and retrieval of information from which it is composed" (p. 1). Essentially a cognitive or mental map is a mapped representation of a person's interpretation of a physical and social environment. Cognitive maps have been used in studies that attempt to understand perceptions of respondents for different social phenomena (i.e., danger, crime, desirability to live and work, etc.) and have been examined using various scales from specific locations to larger geographies (e.g., an apartment complex to an entire country). Often times research that uses cognitive mapping approaches examines differences in the way people perceive spaces to the actual physical space (i.e., compare the map scale, named landmarks, and physical structure). However, cognitive mapping has also been used, although not as frequently, to gain a more qualitative understanding of how people perceive and interpret not just the physical space but also the social space. For instance, cognitive mapping approaches have been used to assess perceptions of crime (Brantingham et. al., 1977) perceptions of danger, (Rengert & Pelfrey, 1998; Nasar & Fisher, 1995), perceptions of perceptions of gang territory (Kennedy, Braga, & Piehl, 1998) and perceptions of crime locations (Brantingham & Brantingham, 1977; Ratcliffe & McCullough, 2001).

In this study, respondents participated in cognitive mapping exercises that were designed to gauge their perceptions of places. Respondents were given two identical paper maps – one for the dangerous area exercise and one for the gang territory exercise. The maps contained cognitive cues in the form of streets with names and also key landmark locations. The landmark locations were those used earlier in the survey to gauge respondent's familiarity with their community. On the map, the landmarks were identified in color with labels. A north arrow and a distance scale were included on the map to help with each respondent's orientation. Respondents were asked to identify the areas under question by drawing on the paper maps using markers of specified color. Examples of the maps given with the survey are included in the copy of the survey that appears Appendix B. Additionally samples of mapping exercises, completed by respondents, are included in Appendix C.

To allow community respondents to become familiar and comfortable reading the map before moving on to questions of dangerous spaces and gang territory, respondents were asked to locate where they lived on the map. The respondents were instructed to place a dot, using a purple marker, in the approximate location of their residence.

Next, by drawing on the map, respondents were asked to identify areas (using a specified colored marker) where they would not feel safe going, both during the day and at night. Respondents were then asked to identify areas on the map where they would advise someone who is not from the community not to go. Respondents were not directed on the size and shape of the areas to mark. Instead, participants were able to assess the whole neighborhood and mark areas as small or large as they wished. In an attempt to tap into each respondent's cognitive reasoning, the survey also included an open-ended question asking why they would advise an outsider to stay away from these areas. Respondents were not directly asked to identify crime cool spots. Instead these variables were derived from the areas that respondents left unmarked on the map. A better detail of cool spot measurement is included in the next chapter.

Interviewer Evaluation

Given the sensitive nature of the survey topic and the retaliation concerns among residents, it was anticipated that respondents would be hesitant to talk about problems and issues plaguing their communities. Researchers anticipated respondents would be uncomfortable and perhaps even scared during the interview, which could potentially cause them to answer questions dishonestly or even refuse to answer questions entirely. The survey authors were also aware that some of the technical aspects of the survey could cause problems. Specifically, there was concern about the literacy levels and map reading capabilities of respondents. Likewise, since the authors of the survey were not native to Trinidad and Tobago, researchers worried that the question wording might not be clear to respondents. Moreover, they anticipated skepticism from respondents regarding the use of an audio recording device. Therefore, once an interview was complete and the respondent had left the room, survey administrators completed a questionnaire on interviewer observations. This was done so that behavior indicators could be examined as a potential explanation to the survey results.

First, survey administrators were asked to rate interviewee behavior during the survey (see instrument in Appendix A). For example, interviewers were asked to indicate whether the respondent remained attentive throughout the survey, if the respondent remained cooperative throughout the survey, if the respondent needed clarification with questions or maps in the survey, if respondents seemed forthcoming with information throughout the survey, if respondents seemed nervous or reluctant to answer questions on the survey, if respondents seemed to use road and landmarks to identify dangerous places and gang areas throughout the survey, and if respondents seemed aware of the audio recording device throughout the survey.

Interviewers were then asked two open ended questions about the interview. The first was an open ended question that asked them to list any questions respondents seemed reluctant to answer. Second, survey interviewers were given an open ended question that asked for additional comments regarding the interview. During training, survey administrators were instructed to include any reflections about the interview that might be useful. Interviewer observations were interesting because they were able describe respondents actions and reactions throughout the course of the survey. For example, interviewers noted things such as, “Respondent appeared to know the questions before they were asked. He was quite nervous and kept looking around especially for the start of the interview. Respondent also appeared to be on some form of drugs as he was acting 'strange” and “Gave information freely on how the gangs do their work.” This question also allowed respondents to note instances or events they thought to be interesting or that might affect the outcome of the survey in one way or another. One interviewer commented, “Respondent did not want to give too much information. He was very vague and he also wanted to replay the tape to insure he did not say anything wrong.” Another noted, “I felt that this respondent was somehow part of a gang and came to see for himself what was going on here.”

Overall, this information was useful in understanding why some respondents refused to participate in the mapping exercises or why there might be inconsistencies from the actual survey and the responses on the mapping exercise.

Crime Data

In this study, two sets of crime data are used to derive dependent variables for this study. The two data sets come from the same data source, the E-999 calls for service data, but represent different crime phenomenon. Specifically, the first data set contains the general crime calls for service, while the second dataset includes those calls that pertain to violent personal crimes.

To obtain the final dependent measures (the hot and cool crime spots) the counts from both datasets were joined to the street segments to diagnose the hot and cool crime spots. Once this was accomplished, I scored respondents on how well they accurately identified hot and alternatively cool spots of crime within their respective neighborhood. I will review this process more thoroughly in Chapter Five. Below I detail each of the data sources.

E-999 Emergency General Crime Call Data

The first dataset contains calls for service and represents all calls made to the E-999 emergency call center for general crimes, including both violent and non-violent crimes. The call types in the E-999 system can range from a fire to a violent crime to a traffic accident. Fields in this dataset include x and y coordinates, the caller's name, address, and phone number, a text description of the location of the event, the date and time of the call, the crime type and code of the call, a call description, and a cross-street field. A cross-street field is included in the dataset because Trinidad and Tobago has no standardized address system. Thus, callers were asked to give a cross-street so that E-999 responders could find the location of the activity more easily.

All in all, the E-999 dataset contains 436,662 calls for service that occurred between July 13, 2002 and September 14, 2007. However, less than half (203,918 or

47%) actually have x and y coordinates that would allow the call for service to be mapped. Moreover, there were issues with call data from the years 2002 and 2003 and with the cross-street information. The 2002 and 2003 data was incomplete due to call system failures. Additionally, in many cases the cross street information did not include street names but instead specific landmarks relative to that incident location. Thus, for the purposes of this research, a subset of data from a two-year period, January 1, 2004-September 14, 2007 (the last available date) which contain x,y coordinates are used. This was done to by-pass the recording problems with the call data had been resolved by this time and include cases that had accurate location information.

From January 1, 2004 to September 14, 2007, there are 7,691 crime calls for service that occurred within the study areas. This final cut of the data is the data that is used to determine the “hottest” and “coldest” spots of general crime in the study areas. Below, Table 4.3 illustrates the frequencies of the final subset of general crime calls from within the study area during the selected time period.

Table 4.3 – Distribution of General Crime Calls in E-999 Calls for Service Data

Call Type	Count	Percent
Armed With Fire-Arm/Ammunition	34	0.45
Armed With Weapon	508	6.66
Assault	272	3.56
Burglary	16	0.21
Disturbance	2,121	27.79
Domestic violence	1,358	17.80
Fight	405	5.31
House break-in	218	2.86
Kidnapping	8	0.10
Larceny	218	2.86
Man on premises	602	7.89
Murder	48	0.63
Rape	19	0.25
Robbery	273	3.58
Shooting	411	5.39
Stolen Vehicle	133	1.74
Suspicious person(s)	315	4.13
Threat	518	6.79
Wounding	154	2.02
Total	7,631	100.00

E-999 Emergency Violent Crime Call Data

Fear of crime and risk assessment literatures indicate it is likely that violent crime hot spots do a better job of informing perceptions of safety and danger (Garofalo, 1981; cite more). Thus, I extracted an additional subset of only violent crimes from the original 7,631 general crimes in Table 4.3. From Table 4.3 we can see that the crimes that may not influence perceptions of safety and danger in the neighborhood make up over half of the crimes included in the construction of the dependent variable measures. Specifically, calls for crimes such as disturbance (27.79%), domestic violence (17.80%), fighting (5.31%), threats (6.79%), and trespassing/man on premises (7.89%) are unlikely to contribute to rationalizations that a place is dangerous and unsafe, yet they make up approximately 65.58% of all crimes included in the original general crime data. Instead, it is more likely that perceptions of safety and fear are often driven by offenses that present a more immediate threat to a person perpetrated by a stranger offender (see Ferraro & LaGrange, 1987).

For these purposes, I created a second set of hot spots that represent the problem locations when only looking at violent crimes against a person. This new crime definition includes just nine violent personal crimes. Table 4.4 lists the frequencies of these offenses. Based on Table 4.4 we can see that the influential crimes have changed considerably. Specifically the offenses of armed with a weapon (29.42%), shooting (23.80%), assault (15.75%) and robbery (15.91%) make up over 80% of the E-999 Emergency calls that pertain to personal violent crime. Interestingly, these crimes mimic many of the replies to respondents concerns about why they would not travel to these areas (see Chapter Six for the summary descriptive of this measure). Consequently, this measure, as well as the general crime hot spot calls, was used to construct four dependent hot spot variables (all of which are detailed further in Chapter Six).

Table 4.4 – Distribution of Violent Crime Calls in E-999 Calls for Service Data

Call Type	Count	Percent
Armed With Fire-Arm/Ammunition	34	1.97
Armed With Weapon	508	29.42
Assault	272	15.75
Kidnapping	8	0.46
Murder	48	2.78
Rape	19	1.10
Robbery	273	15.81
Shooting	411	23.80
Wounding	154	8.92
Total	1,727	100.00

There are potential limitations to using this E-999 crime data that merit attention. Specifically, the data is somewhat problematic because it does not contain location data for all calls for service. Instead, only a portion of crime calls have x and y coordinates. To check for potential biases in the data, I compared the percentages of calls that were matched to all of the unmatched calls in the dataset by crime type (see Appendix D). For all of the crimes used to create hot spots in this study, the percentage matched was as good or better than the percent of unmatched calls per crime type from the E-999 dataset. Although this initial examination of bias in the E-999 calls for service data indicates that there might not be bias in whether the call data includes x,y information, there are still potential limitations to this data.

I then checked for location bias among the E-999 call data with location information by comparing homicides in the E-999 dataset to those collected by the TTPS Project team from police incident records. Initial comparisons of the data revealed that of the 48 homicide E-999 calls for service, less than half (20) actually intersected street segments associated with homicide incidents obtained from the TTPS records (N=130).

Overall, there were substantial mismatches among the two datasets, although the proximity of some street segments were close (see map in Appendix D).

However, before we discredit the validity of the E-999 data based on this potential location bias, there are some additional details to consider. First, this examination of bias compares two entirely different data sources – one that represents calls for service data (E-999) and one that represents actual crime incident reports of homicide. It is possible that the E-999 data may not contain information for all of the homicides because of low reporting. It is also possible that when reporting a serious violent offense, like homicide, residents might call their police station directly instead of calling the E-999 service (which only started in Trinidad and Tobago in 2002 and had initial problems). Lastly, we need to consider that calls which might, in reality, be linked to homicide incidents are not classified as such by the E-999 dispatchers. It is likely that in many instances, these scenarios were reported as disturbances, woundings, or shootings and were only later classified as homicide incidents. Since there is no way to match calls for service to incident data, these possibilities must remain unexamined.

Furthermore, as with any crime data source there are additional biases to consider. For instance, because much of the area that is under study is reportedly some of the highest in poverty and lower socio-economic status, there is some concern that these calls for service might under-report the crime phenomena in the study areas simply because these residents may not have easy access to telephones. This is may be especially true for instance of violent crime and victimization. This limitation is discussed further in Chapter Seven.

Conclusion

To conclude, the primary data for this study is from a survey of active community residents from selected areas of two Trinidadian communities. These areas were targeted because of the high levels of crime and disorder they experienced (Maguire, et.al, 2009; Johnson, 2007). In an attempt to properly answer the research question, this survey was administered in an interview style. In addition to the survey, respondents were given four cognitive mapping exercises that allowed for open-ended questions to gauge their spatial cognitive processes. Additionally, two cuts of the emergency E-999 calls for service data, general crime and violent personal crime, are also used. These crime data allowed for the identification of the hottest and coolest crime locations within the study areas, a process that I detail further in the next chapter.

CHAPTER 5: DIAGNOSING RESPONDENT ACCURACY

Because the goals of this study, the approach for deriving the dependent variables needs to account for the differences in perceptions among respondents as well as understand how those perceptions relate to specific crime hot and cool spot locations. Moreover, to answer how individual factors influence respondent hot and cool spot accuracy, the dependent constructs need to measure the variability among individual responses.

Constructing dependent variable measures from cognitive maps is somewhat tricky. Most often cognitive mapping research is used to measure perceptions of physical locations (i.e., distance to a city center or a specific physical landmark) and dependent variables are often calculated from measures representing distance and accuracy of the cognitive map to a scaled, computer generated map (Kitchen & Blades, 2002). In other words, this approach often compares individual perceptions to an actual physical phenomenon and not a social or environmental phenomenon such as danger or crime.

Considering the challenges of deriving appropriate measurements from cognitive maps, the most viable solution is a calculation of whether or not respondents mark areas that coincide with crime hot and cool spots. Thus, dependent variables for this study consist of an index score that represents the accuracy with which respondents perceptions (measured by the areas that respondents marked) match to select crime and non-crime locations within the study areas during the day and night.

Before moving on to the study outcomes, it is important to review some information about the study sample. Overall, there were 168 initial responses to the survey. However, there were 12 missing responses to the mapping portion of the survey (i.e., there were responses to the questionnaire portion, but not the mapping portion). Upon investigation, reasons for the missing responses were issues such as respondents refusing to complete the mapping exercise, respondents not capable of completing the mapping exercise (i.e., poor eye sight, illiteracy, etc.) and in two instances lost data. Once I accounted for missing responses to the mapping questions, the valid sample size is 152. Please note, the distributions and percentages reported below are those from the full sample (N=168), unless otherwise noted.

What's Hot and What's Not

The top ten hot spots of both general crime and violent crime, and a random selection of ten cool spots, or places where crime does not occur, were identified. I generated these hot and cool places by identifying the highest crime count street segments using a spatial join within ArcGIS 10.1. Two crime calls for service point shapefiles (one for general crime and one for violent crime) were each spatially joined to the street polyline shapefile to generate two new files containing counts per street segment for each[2]. These final counts were then used to select the top 10 streets for each community containing the highest counts of both general crime and violent crime, as well as the ten randomly selected cool spots for each of the study areas.

I should note here that the mapping questions did not specifically ask respondents about crime hot spots or crime cool spots. Instead these prompts asked respondents where they would not feel safe going during the day and night. As a means to understand the motivation for making unsafe/dangerous areas, respondents were given an open-ended question that asked why they stay away.

The initial coding of the question that asked why respondents marked areas as unsafe yielded five different categories: Crime (27.4%), Danger of Victimization (31.5%), Gang Activity (8.3%), Crime and/or Danger of Victimization and/or Gangs (26.8%) and other (1.8%). This outcome suggests that approximately 94% of the survey sample attributes the lack of safety and dangerousness in these areas to some type of risk associated with crime and criminal activity. I should note that the responses for gang activity is actually quite low compared to concerns about crime and danger of victimization, which when combined represent well over half of the responses alone (58.9%). Based on these results, using these maps to determine perceptions of crime and non-crime areas appears to be well supported. Essentially, the places respondents marked on a map are overall a good representation of those that they claim harbor crime and

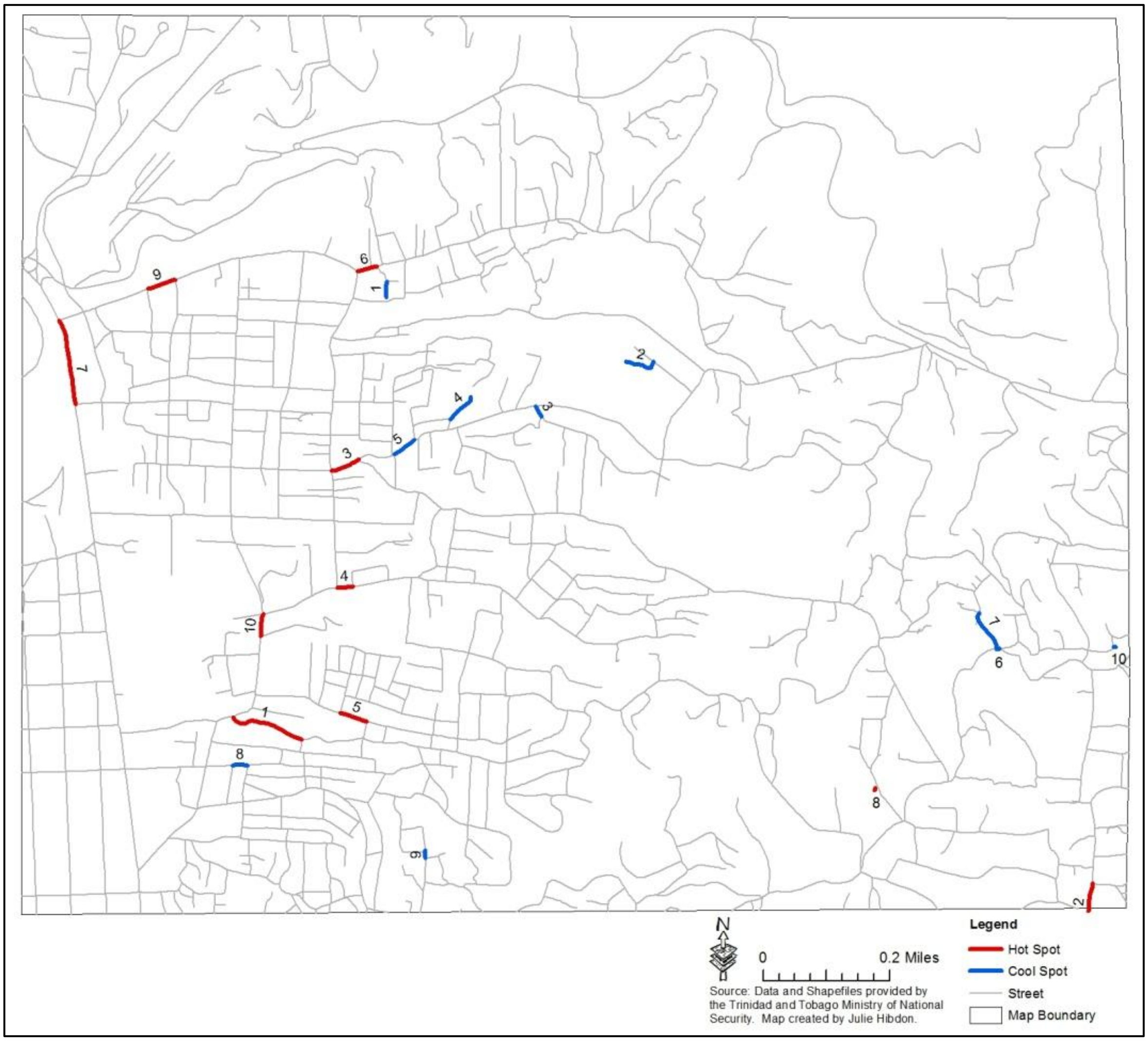
[2] In addition to diagnosing the counts per street segment, I also standardized the count score by street length. The results indicated that even when controlling for street length, there were no changes in the hot spots for either general or violent crime.

victimization risks and those that are not marked seem to represent those locations that they consider safe.

Cool crime spot locations were identified by first selecting all of the street segments with zero crime incidents for the study period for each of the two communities. I then saved and exported two files, one for Belmont and one for Morvant, of the cool crime spots. Using SPSS 18, I randomly generated 10 street segments for each neighborhood. Finally, I brought the 10 randomly selected segments back into ArcGIS 10.1 using a street ID join.

Now that I have detailed the operationalization of the crime hot and crime cool spots, it is important to review some basic findings about the hot and cool crime locations. It is also necessary that we look at these basic findings before moving into a review of the construction details and descriptive statistics for the dependent measure indices. Figures 5.1 through 5.4 illustrate the location of general crime hot (Figures 5.1 and 5.3), violent crime hot (see Figures 5.2 and 5.4) and cool crime spots, which can be matched with its corresponding number (red segments, 1-10=hot spots); (blue segments, 1-10=cool spots).

Figure 5.1 –General Crime and Random Cool Crime Spots in Belmont



As the Belmont map illustrates, the top 10 general crime hot spots tend to be concentrated more to the western portion of the study map. Essentially, all but two of the general crime hot spots are located there. The other two top general crime hot spots are in the southeastern portion of Belmont (HS #2 and HS #8). I should note that HS #2 is located in an area that overlaps with the Morvant map. It is also worth noting that none of the Belmont crime hot spots are connected directly to one another; however some are quite close and in some instances the hot spots lie on the same stretch of road (i.e., HS #6 and #9).

The randomly selected cool spots seem to be dispersed a little more evenly throughout the study area, although there appears to be a bit of a concentration in the northern center of the map. Two cool spots, CS #6 and CS #7 are connected.

Figure 5.2 –Violent Crime and Random Cool Crime Spots in Belmont

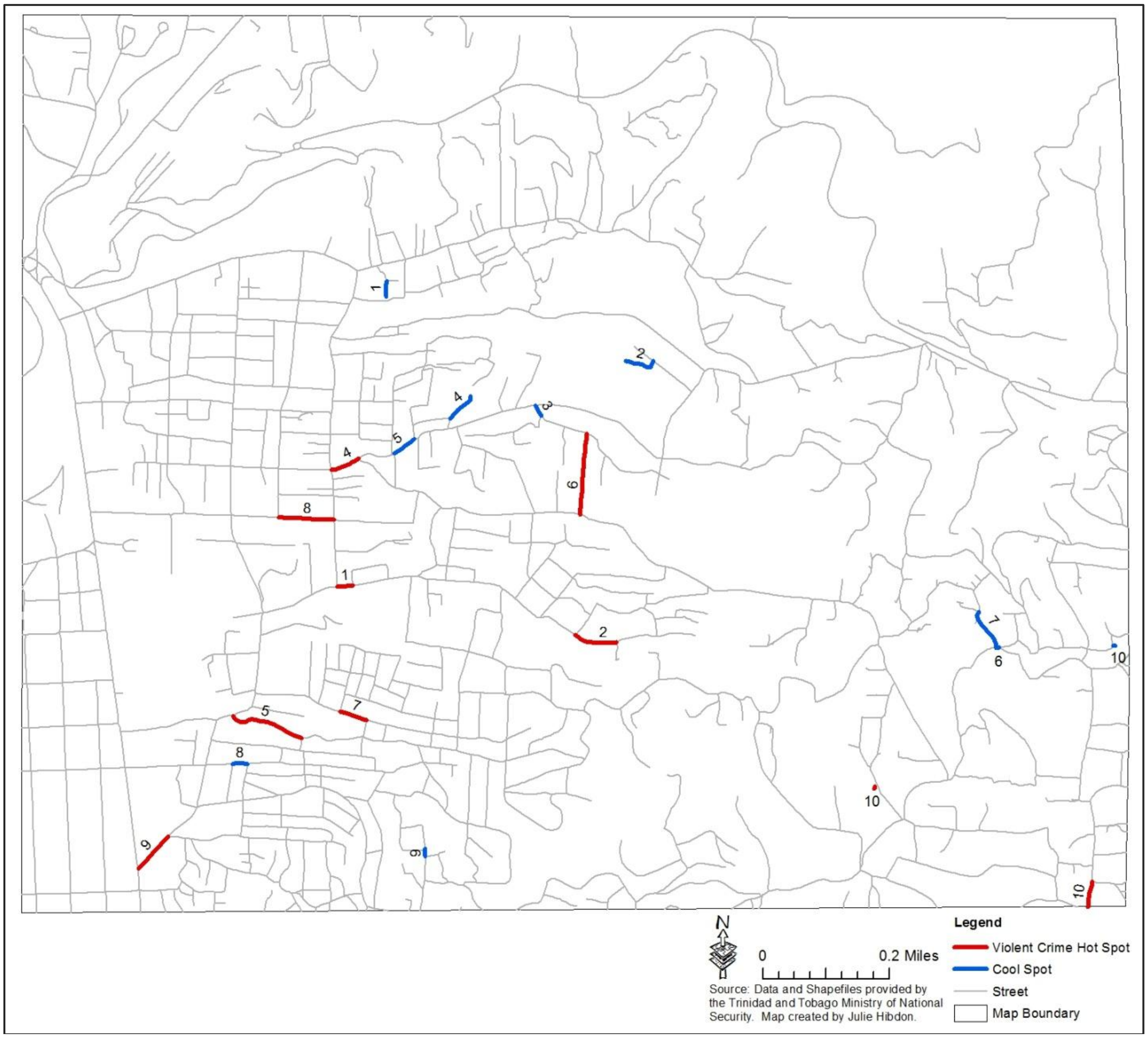


Figure 5.2 illustrates the locations of the violent crime street segments along with the same randomly generated crime cool spots for Belmont. When looking at the differences between Figures 5.1 and 5.2 we can see that the many of the locations of the general crime hot spots and violent crime hot spots in Belmont are the same street segments. However, there is a noticeable shift in the locations when moving from general crime to violent crime. Specifically, in the violent crime map (see Figure 5.2),

there are no longer hot spots located in the upper western portion of the neighborhood. Instead, there are now two hot spot segments in the center portion of the map (see HS #2 and HS#5). Also, we have a new hot spot segment in the south western portion of the neighborhood (see HS#8).

Figure 5.3 –General Crime and Random Cool Crime Spots in Morvant

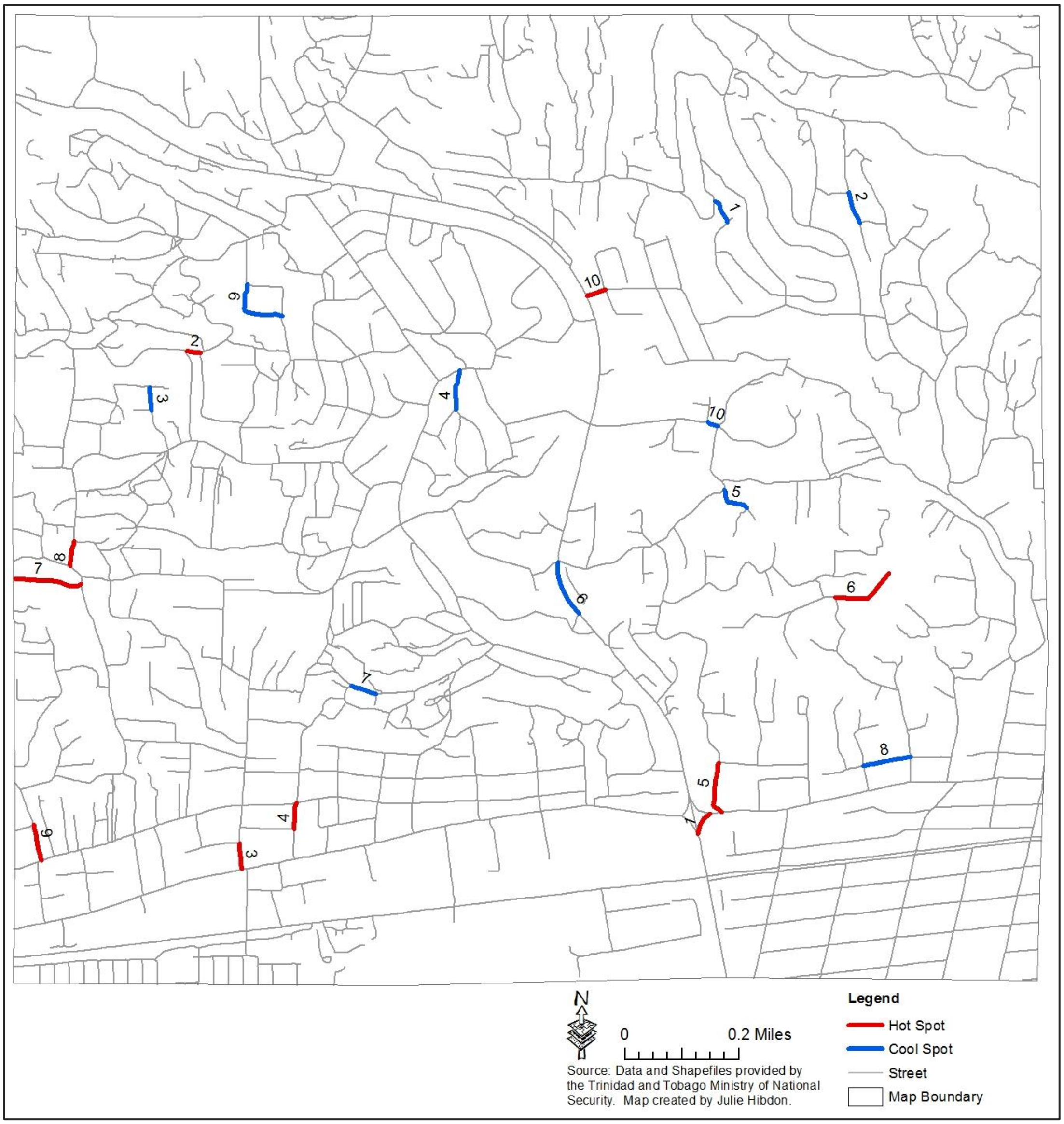


Figure 5.3 is a copy of the Morvant map that was given to survey respondents. Like the Belmont map, the 10 study hot spots are marked with red and the 10 randomly selected cool spots are highlighted in blue and marked with identification numbers. A quick examination of the map reveals that many of the top general crime hot spots in

Morvant are in the southern portion of the community, not far from a major road thoroughfare. Unlike the Belmont map, the randomly selected cool crime segments in Morvant seem to be evenly spread throughout the map area. Crime hot spots #3 and #10 border the area of Belmont where Belmont hot spot #2 is located. As with the Belmont general crime and violent crime hot spots, no streets are directly connected; however, Morvant general crime hot spots #5 and #7 are remarkably close. Likewise, all of the randomly selected cool crime segments in Morvant are separated by at least one additional street segment. Additionally, it is worth noting that for both the Belmont and Morvant maps, there are instances where there is not much distance between hot and cool crime locations.

Figure 5.4 – Violent Crime and Random Cool Crime Spots in Morvant

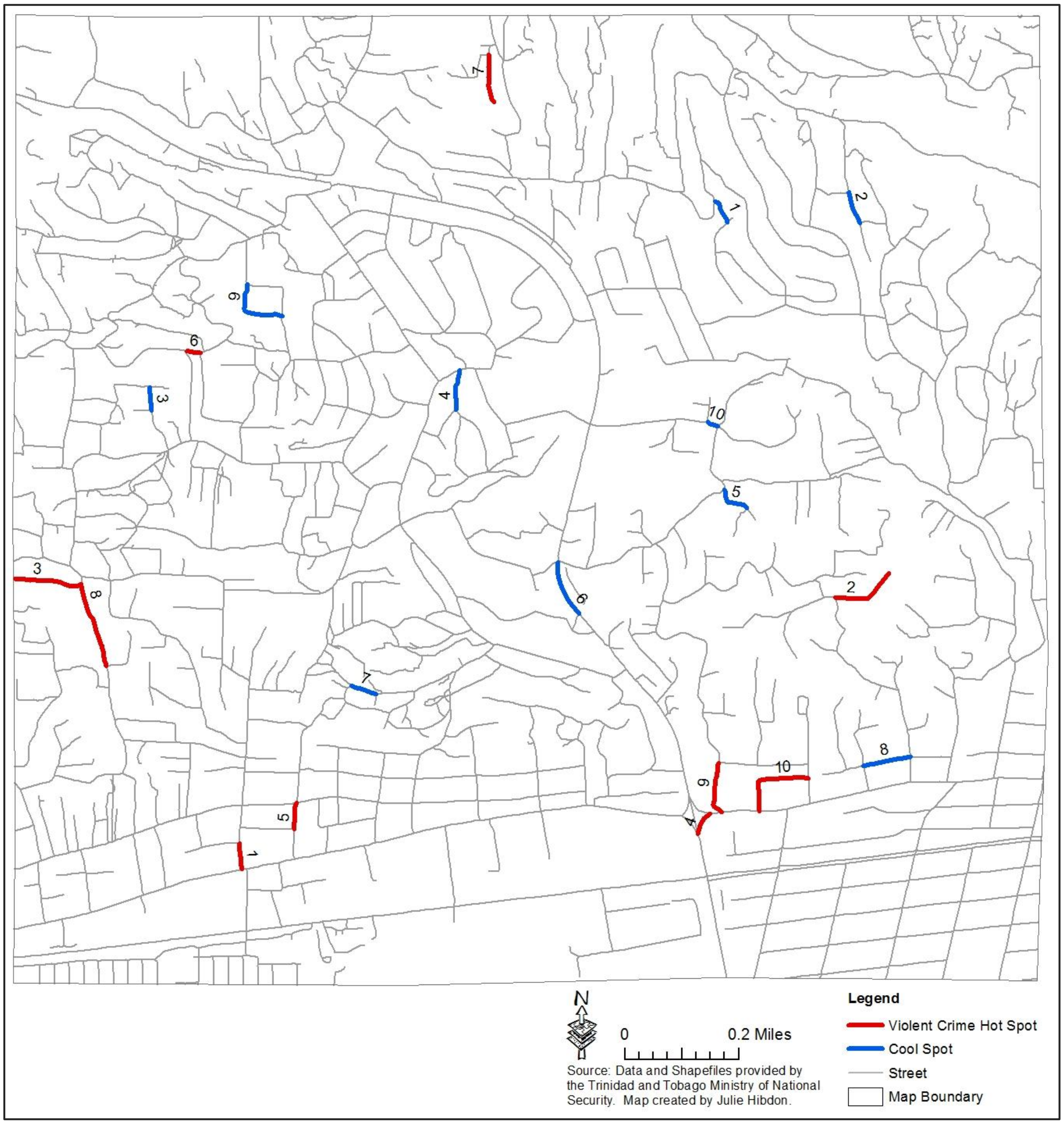


Figure 5.4 illustrates the distribution of the violent crime hot spots in Morvant. Similar to Belmont, many of the general crime street segments and the violent crime segments overlap. However, there are a few differences. For instance, hot spot segment #1 (north-central portion of the map) and hot spot segment #4 (western portion of the

map) are new crime hot spots. Also, hot spot segment #10 in the south-eastern portion of the map. Unlike the general crime hot spots, there are some violent crime hot spot street segments intersect (see segments HS#9 and HS#4).

Testing Respondent Accuracy

Although the maps are useful in visualizing the locations and proximity of the hot and cool spots, they do not give us a good sense of the crime incidents at these locations, nor do they give us a sense of how often survey respondents included these locations in their assessments of the neighborhoods. To help answer the first research question, I first examine the accuracy with which respondents indentify hot crime locations in their neighborhood. To do this, I created tables that illustrate the prevalence of crimes at each hot spot as well as the percentage of respondents that correctly identified each location. Tables 5.1-5.3 below illustrates the frequency of respondents' identification of each hot spot and cool spot. These tables note the number of crimes that occurred at each.

Table 5.1 – Belmont General Crime Hot Spot Identification Frequencies

Belmont Hot Spot	Number of Crimes	% of Correct Identifications Day	% of Correct Identifications Night
1	204	11.4%	17.0%
2	142	15.9%	26.1%
3	115	10.2%	11.4%
4	108	8.0%	18.2%
5	101	11.4%	15.9%
6	98	11.4%	14.8%
7	88	1.1%	2.3%
8	88	20.5%	25.0%
9	75	4.5%	4.5%
10	74	5.7%	9.1%

In Table 5.1, the most noted general crime hot spot in Belmont was hot spot #8 (8th worst), approximately 20.5% of respondents accurately identified this location as problematic. The second most noted hot spot by Belmont respondents was hot spot #2 (15.9%). Hot spot #2 was also the second worst ranked for crime. For the night identification, hot spots #8 and #2 are still the top two locations identified by respondent, although they switch order. Note that for all of the general crime hot spots the accuracy of identification by respondents improved from day to night. For two street segments (HS #9 and HS #10) less than 10% of the sample considered these locations to be problematic and are accurately reflecting their rank of 9th and 10th place. Here we also see the accuracy of general crime hot spot identification either staying constant or improving from day to night.

Table 5.2 – Belmont Violent Crime Hot Spot Identification Frequencies

Belmont Hot Spot	Number of Crimes	% of Correct Identifications Day	% of Correct Identifications Night
1	43	7.6%	18.2%
2	28	9.1%	15.9%
3	27	20.5%	25.0%
4	26	10.3%	11.4%
5	22	11.4%	17.0%
6	20	22.7%	26.4%
7	19	11.4%	15.9%
8	16	3.4%	8.0%
9	16	4.5%	12.5%
10	16	15.9%	26.1%

When comparing the frequencies between Tables 5.1 and 5.2 it appears that respondents do a better job of including crime hot spots in their cognitive maps of violent crime versus general crime. The most frequently identified host spot by Belmont respondents during the day included hot spot #3 and hot spot #6. These locations, along with hot spot #10 are the most commonly identified violent crime hot spot locations identified by Belmont respondents at night. For the day map, the least included violent crime hot spots were hot spot #8 and hot spot #9. For the night map, respondents were least likely to identify violent crime hot spots hot spot #8 and hot spot #4. As with the general crime hot spots, accuracy scores for the violent crime hot spots improved for every hot spot from the day map to the night map.

Table 5.3 – Belmont Cool Spot Identification Frequencies

Belmont Cool Spot	% of Correct Identifications Day	% of Correct Identifications Night
1	89.8%	87.5%
2	94.3%	88.6%
3	87.5%	77.3%
4	92.0%	86.4%
5	89.8%	86.4%
6	86.4%	79.5%
7	86.4%	79.5%
8	87.5%	79.5%
9	94.3%	89.8%
10	90.9%	89.8%

The picture for the Belmont cool spot identification is very different from that of general and violent crime hot spots. Specifically, a vast majority of respondents accurately identified crime cool spots in their day and night maps. The most correctly identified cool spot was a tie between cool spots #2 and #9. The least commonly identified during the day was a tie between cool spot #6 and cool spot #7. This makes sense, considering that these cool spots intersect (see Figure 5.1). Contrary to the change in hot spots from day to night, the accuracy of cool spot identification decreased for each of the 10 randomly selected cool spots in Belmont from day to night.

Tables 5.4-5.6 report these same statistics for Morvant map responses. The most noted hot spot in Morvant, for both day and night, is hot spot #8 (20.6% day; 33.8% night). This location actually sits just east of the area that the two neighborhood maps share. Interestingly, hot spot #7, which is just south of hot spot #8, tied for third place. Again, from day to night we see consistent increases in the accuracy of general crime hot spots by Morvant respondents.

Table 5.4 - Morvant General Crime Hot Spot Identification Frequencies

Morvant Hot Spot	Number of Crimes	% of Correct Identifications Day	% of Correct Identifications Night
1	284	5.9%	13.2%
2	230	14.7%	17.6%
3	225	7.4%	13.2%
4	185	4.4%	8.8%
5	183	14.7%	19.1%
6	180	16.2%	26.5%
7	153	14.7%	19.1%
8	142	20.6%	33.8%
9	128	8.8%	11.8%
10	126	8.8%	22.1%

The accuracy statistics for the violent crime hot spots are presented in Table 5.5 below. As we can see, the most frequently identified violent crime hot spot for both the day and the night is violent crime hot spot #7, which is located in the most northern section of the community in a neighborhood called Never Dirty. The second most accurate location identified by the Morvant respondents is hot spot #2, which is the second hottest violent crime location in the community. Violent crime hot spot #2 is the most eastern crime location on the violent crime map (see Figure 5.4). Surprisingly, one of the least commonly identified hot spots during the day is the location that contains the most violent crime in Morvant (HS #1). Even though the accuracy rank of this location improves with the night question, it is still not one of the most commonly included hot spots in respondents' perceptions of dangerous areas. As with the other crime hot spot tables, there is a noticeable increase in the percent of correct identifications from the day to the night.

Table 5.5 – Morvant Violent Crime Hot Spot Identification Frequencies

Morvant Hot Spot	Number of Crimes	% of Correct Identifications Day	% of Correct Identifications Night
1	61	4.7%	13.2%
2	59	16.2%	26.5%
3	54	14.7%	19.1%
4	48	3.8%	13.2%
5	44	4.4%	8.8%
6	43	14.7%	17.7%
7	42	22.1%	27.9%
8	41	13.2%	16.1%
9	36	14.7%	19.1%
10	36	7.4%	10.3%

Morvant respondents also did a good job of correctly identifying crime cool spots in their community. As Table 5.6 illustrates, the vast majority (>85%) of Morvant respondents correctly identified these locations as non-problematic. The most accurate responses were for cool spot #4 in which only one respondent incorrectly identified it as a problem area. This result is not surprising in that this street segment is within a block of the Morvant police station. The accuracy percentage for this crime cool spot was maintained even when asked about dangerous or unsafe areas at night. As with the

Belmont cool spots statistics, there is still a noticeable decrease in the percent accurate from day to night for all of the other nine crime cool spots.

Table 5.6 – Morvant Cool Spot Identification Frequencies

Morvant Cool Spot	% of Correct Identifications Day	% of Correct Identifications Night
1	95.6%	85.3%
2	92.7%	86.8%
3	92.7%	88.2%
4	98.5%	98.5%
5	88.2%	83.8%
6	92.0%	77.9%
7	86.8%	82.3%
8	95.6%	92.6%
9	94.1%	88.2%
10	94.1%	92.6%

Hot and Cool Spot Indices

Next, I created indices of hot and cool spot accuracy for each of the study respondents. Specifically, six scores were created which represent: (1) the accuracy of identifying the top 10 general crime hot spots during the day; (2) the accuracy of identifying the top 10 violent crime hot spots during the day; (3) the accuracy of identifying the 10 randomly selected crime cool spots during the day; (4) the accuracy of identifying top 10 general crime hot spots at night; (5) the accuracy of identifying top 10 violent personal crime hot spots at night; and (6) the accuracy of identifying the 10 randomly selected cool crime spots at night. The construction and meaning of each of these measures is detailed below.

General Crime Hot Spot Index for Day – Respondents were asked to mark on the paper maps where they would not go during the day. Responses were coded into 10 dichotomous variables, with each variable representing a hot spot. Responses were then assigned a value of 1 if their marking to the question included the crime hot spot and 0 if it did not. These 10 dichotomous variables were then summed to obtain the proportion of correctly identified dangerous places. This additive index represents the hot spot index score for the day mapping exercise.

General Crime Hot Spot Index for Night – Like the index score for hot spot day responses, the same process was be carried out for perceptions about areas at night. All general crime night accuracy variables were then summed by ten to obtain the hot spot index score for night.

Violent Crime Hot Spot Index for Day – To create a measure for the violent crime day index, I again used a dichotomous coding scheme to create 10 new violent crime hot spot measures for each study area (one representing each violent crime hot spot). Within the dichotomous coding a score of 0 meant that the violent crime hot spot not in respondent's day map markings and a score of 1 indicated that the violent crime hot spot had been included. To obtain the violent crime hot spot index, I then summed the values of the 10 dichotomous measures.

Violent Crime Hot Spot Index for Night – As with the other three hot spot measures, this index was created by first creating 10 dichotomous measures that represent whether respondents included the designated violent crime hot spot in their cognitive night map of dangerous/unsafe areas (0=not included in night map; 1=included in night map). Then, each of the 10 dichotomous measures were summed in order to obtain the violent crime hot spot night index.

Cool Spot Index for Day – As with the hot spot variables, I created a dependent variable representing the number of cool spots that respondents included in areas they considered dangerous or unsafe. Similar to the hot spot index scores, the number of cool spots that were not included in markings on the map of dangerous or unsafe areas during the day were summed, where a score of 10 meant that respondents considered all of the randomly selected areas to be unsafe and 0 which meant that respondents did not consider any of the areas to be unsafe. For intuitive purposes, this sum was then reverse coded (0=completely inaccurate; 10=totally accurate) to obtain the final index score.

Cool Spot Index for Night – As with the cool spot night dependent variables measure, I created an additive index score that represents whether respondents properly marked cool spots at night. Again, this measure was derived from a dichotomous coding of each location (0=cool spot not in unsafe area; 1=cool spot in unsafe area). To calculate the proportion index, the scores were summed. The sum value was then reverse coded so that the score properly reflected the number of cool spots the respondent correctly identified as such.

The preliminary descriptive statistics for each of the six hot spot accuracy scores are included in table 5.7 below. For three of the six (i.e., Hot Spot Day Score, Cool Spot Day Score, and Cool Spot Night Score), accuracy scores ranged from 0 to 10. The dependent variable Hot Spot Night Score ranges from 1 to 12, due to the overlap of area in the between the Belmont and Morvant maps. Specifically, one Morvant respondent drew areas that also encompassed Belmont Hot Spot #2. There were no overlaps during the day drawings. Additionally, each dependent measure had a mean of no more than

1.49 (Hot Spot Day=1.13l; Hot Spot Night=1.49). This low mean for scores that range from 1 to 10 and 12 essentially indicates that the scores are highly skewed toward the lower range of scores (i.e., 0,1,2).

A glance at the skewness and kurtosis statistics back this finding. For a normal distribution, the skewness statistic should be at or close to 0. However, for all six dependent measures, the skewness statistic is over 2.0, indicating a highly skewed distribution. Similarly, for a normal distribution, the kurtosis statistic, which is an indication of the peakedness of the distribution, is typically at or around 0. Again, each of the dependent measures in this study are well above 0 (lowest is 5.81) indicating a sharply, peaked, skewed distribution. For histograms and frequency tables of the dependent measures, please refer to Appendix E.

Table 5.7 - Detail Descriptive Statistics of Four Dependent Variables

	N	**Mean**	**SD**	**Min**	**Max**	**Skewness**	**Kurtosis**
Hot Spot Day Score – Gen Crime	157	1.13	2.07	0	10	2.62	10.14
Hot Spot Night Score – Gen Crime	157	1.57	2.27	0	12	2.07	7.56
Hot Spot Day Score – Violent Crime	157	1.24	2.11	0	11	2.53	10.00
Hot Spot Night Score – Violent Crime	157	1.80	2.36	0	11	1.76	5.81
Cool Spot Day Score	157	9.06	1.78	0	10	-3.08	14.43
Cool Spot Night Score	157	8.60	2.10	0	10	-2.05	7.24

From the variable descriptives (see Appendix E), the zero score count is relatively high (ranging from 57.14% to 41.67%) for the four hot spot dependent measures. These numbers tend to suggest that respondents are more likely to identify one or more hot spots when asked where they would not go during the night (58.33%) versus the day (45.24%). However, as these numbers suggest, a good portion of the sample was unable to identify even one crime hot spot during the day or the night.

Overall, the accuracy with which respondents identified cool spots is very different. Specifically, 57.14% respondents were 100% correct in not including even one hot spot in areas they considered dangerous (45.83% were 100% correct at night). Moreover, 90.48% of the day responses and 86.90% of the night responses included four or fewer cool spot locations in the areas they consider to be unsafe or dangerous.

Testing for Dependent Variable Differences

Finally, before we can move into an analysis of these measures, it is important to look at a simple correlation table to see how the six dependent variable measures relate to one another. Essentially, we would expect that a person's ability to identify crime and non-crime locations would be positively correlated – essentially that if they know where to go then they would also know where not to go. Yet, the correlation statistics in Table 5.8 illustrate the relationship between the ability of respondent's to identify hot and cool crime locations is not as predicted. This output again suggests that respondents are much better at properly marking cool spots than hot spots. There are a number of possible reasons to explain this phenomenon.

One possibility is that respondents are accurately identifying crime cool spots by chance. This is likely considering the survey mapping questions did not specifically ask respondents to identify crime cool spots; instead, it only required respondents to mark locations that they considered unsafe or dangerous. For instance, it may be the case that respondents have a high percentage of accuracy because traditionally, there are many crime cool spots in a given set of street segments. In this study, this is no different.

When examining the cool spot distribution of general crime (i.e., streets with a general crime count of zero), I find that 63.70% of the 1,210 Belmont street segments are cool and 71.26% of the 1,437 street segments in Morvant are cool. For violent crime, the percentage of cool crime spots increases. This is what we would expect considering the reduction in the number of crimes for violent versus general crimes. Specifically, for Belmont 79.42% of street segments are crime cool spots (i.e., streets with a violent crime count of zero) and 84% of street segments in Morvant are cool crime spots.

Adding to this explanation is the possibility that overall, respondents are marking a relatively small area of the map, making it easy to miss one of the 10 crime hot spots and difficult to miss the one of the 10 randomly selected crime cool spots. Although the range for the map area is 0-100%, both day and night maps had a mean response of less than 10%, supporting this suspicion. The next section contains a detailed discussion of the percent of the marked measure.

Table 5.8 – Dependent Variable Correlation Matrix

		Gen. Crime Hot Spot Day	Cool Spot Day	Gen. Crime Hot Spot Night	Cool Spot Night	Violent Crime Hot Spot Day	Violent Crime Hot Spot Night
Gen. Crime Hot Spot Day	Pearson Corr.	1	-.766**	.829**	-.534**	.947**	.766**
	Sig. (2-tailed)		.000	.000	.000	.000	.000
	N	157	157	157	157	157	157
Cool Spot Day	Pearson Corr.	-.766**	1	-.688**	.998**	-.783**	-.646**
	Sig. (2-tailed)	.000		.000	.000	.000	.000
	N	157	169	157	169	157	157
Gen. Crime Hot Spot Night	Pearson Corr.	.829**	-.688**	1	-.709**	.790**	.914**
	Sig. (2-tailed)	.000	.000		.000	.000	.000
	N	157	157	157	157	157	157
Cool Spot Night	Pearson Corr.	-.534**	.998**	-.709**	1	-.572**	-.723**
	Sig. (2-tailed)	.000	.000	.000		.000	.000
	N	157	169	157	169	157	157
Violent Crime Hot Spot Day	Pearson Corr.	.947**	-.783**	.790**	-.572**	1	.820**
	Sig. (2-tailed)	.000	.000	.000	.000		.000
	N	157	157	157	157	157	157
Violent Crime Hot Spot Night	Pearson Corr.	.766**	-.646**	.914**	-.723**	.820**	1
	Sig. (2-tailed)	.000	.000	.000	.000	.000	
	N	157	157	157	157	157	157

** Correlation is significant at the 0.01 level (2-tailed).

Because of the consistent differences in the day and the night results for each of the dependent measures (see Tables 5.1-5.6) and the significant and strong correlations between the six dependent measures (see Table 5.8), I ran a paired t-tests to see if the differences were significant. This addressed findings of past literature by testing whether accuracy scores really differ based on the time of day. Moreover, if the measures are not significantly different, six different dependent variables may not be necessary. However, if the night and day measures are different, as was hypothesized earlier, it is critical that all six dependent measures be calculated and used in later analysis.

To test for these differences, I used a paired t-test to compare the mean of the two accuracy scores. For both general crime ($t= -4.354$, $p=0.000$) and violent crime ($t= -5.103$, $p=0.000$), respondents were significantly better at night identification than they are at daytime identification (see Table 5.9). On the other hand, respondent accuracy scores for crime cool spots are significantly worse for night map responses than they are for day map responses (t=3.620, p=0.000).

Table 5.9 – Paired T-Test Results by Time of Day

		Paired Differences							
					95% Confidence Interval of the Difference				
		Mean	Std. Dev.	Std. Error Mean	Lower	Upper	t	df	Sig. (2-tailed)
Pair 1	General Crime HS– Day General Crime HS– Night	-.446	1.283	.102	-.648	-.244	-4.354	156	.000
Pair 2	Violent Crime HS–Day Violent Crime HS–Night	-.554	1.361	.109	-.769	-.340	-5.103	156	.000
Pair 3	Cool Spot – Day Cool Spot – Night	.459	1.587	.127	.208	.709	3.620	156	.000

I then decided to use the paired t-test analysis to see if, when holding the time of day constant, accuracy scores improved for violent crime measures compared to general crime measures. Again, this analysis tests the conclusions of prior literatures that find that violent crimes do a better job of informing perceptions of fear and risk.

Indeed, the results in Table 5.10 confirm that for both day and night responses, respondents' accuracy scores for violent crime hot spots are better than those for general crime. This result suggests the violent crimes may have a larger influence on whether respondents accurately identify crime hot spots in their perceptions of unsafe and dangerous locations throughout the neighborhood.

Table 5.10 – Paired T-Test by Crime Classification

		Paired Differences							
					95% Confidence Interval of the Difference				
		Mean	Std. Dev.	Std. Error Mean	Lower	Upper	t	df	Sig. (2-tailed)
Pair 1	General Crime HS-Day Violent Crime HS-Day	-.115	.679	.054	-.222	-.008	-2.115	156	.036
Pair 2	General Crime HS-Night Violent Crime HS - Night	-.223	.965	.077	-.375	-.071	-2.895	156	.004

Last, before moving on to the inferential tests examining the influence of individual factors on perceptions of hot and cool crime locations, I wanted to confirm there were no community differences in the dependent variables used in this study, which could affect the generalizability of the study findings. Therefore, I ran an independent samples t-test by community (1=Belmont, 2=Morvant). The results are reported in Table 5.11 below. As the results indicate, there are no significant ($p<.05$) community differences in any of the dependent measures.

Table 5.11 – Independent Samples T-Tests by Community

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Diff.	Std. Error Diff.	Lower	Upper
General Crime HS-Day	Eq. var. assumed	4.416	.037	-1.317	154	.190	-.439	.333	-1.098	.220
	Eq. var. not assumed			-1.273	121.5	.205	-.439	.345	-1.122	.244
General Crime HS-Night	Eq. var. assumed	5.871	.017	-1.691	154	.093	-.613	.362	-1.329	.103
	Eq. var. not assumed			-1.634	121.8	.105	-.613	.375	-1.355	.130
ViolentCrime HS-Day	Eq. var. assumed	3.315	.071	-1.225	154	.222	-.417	.340	-1.090	.255
	Eq. var. not assumed			-1.186	123.1	.238	-.417	.352	-1.113	.279
Violent Crime HS-Night	Eq. var. assumed	4.348	.039	-1.504	154	.135	-.566	.376	-1.308	.177
	Eq. var. not assumed			-1.462	126.1	.146	-.566	.387	-1.331	.200
Cool Spot Day	Eq. var. assumed	.114	.736	-.226	154	.821	-.066	.290	-.638	.507
	Eq. var. not assumed			-.223	136.7	.824	-.066	.293	-.645	.514
Cool Spot Night	Eq. var. assumed	.053	.818	-.550	154	.583	-.186	.339	-.857	.484
	Eq. var. not assumed			-.548	142.1	.585	-.186	.340	-.860	.487

Conclusion

Overall, the purpose of this chapter was twofold. First, it presents diagnostics on the accuracy with which respondents are able to identify hot and cool crime locations in their community. The results suggest that overall respondents are not very accurate at identifying general or violent crime hot spots in their community. Yet, accuracy scores improve when using violent crime versus general crime measures. Moreover, these findings suggest that the time of day also influences the accuracy with which respondents identify hot and cool crime locations. Specifically, it was found that respondents are better at identifying both general and violent crime hot spots and worse at identifying cool spots at night.

In addition to testing respondent accuracy, this chapter thoroughly detailed each of the dependent measures that will be used in the inferential analysis that will test how individual factors influence a respondent's ability to accurately identify crime and non-crime locations in their neighborhood. The next chapter, Chapter Six, details each of the independent measures and the analysis techniques that will be used to answer this second research question.

CHAPTER 6: TESTING THE IMPACT OF INDIVIDUAL PREDICTORS

Now that we have addressed the first study question, it is necessary to move into a discussion of the individual predictors and the analysis technique for the second inquiry. Each of the sections below detail the study measures and describe how each independent variable is operationalized for this research. Additionally, I have included the descriptive analyses for each independent variable measure. Finally, this chapter includes a detailed review of the analysis models and techniques that are used in Chapter Seven.

The current study uses three sets of independent variables. Specifically, variables related to individual demographics, individual predictors of disorder and crime, and individual neighborhood and familiarity are tested. All of the independent variables for this study are from the Community Problems and Issues Survey (CPIS) discussed in Chapter Four. Figure 6.1 contains a short description of each of the independent measures. A detailed description of each variable, including its measurement and summary statistics, is included below.

Figure 6.1 – List of Individual Level Predictors

Characteristic	Composition
Individual Demographics	
• Age • Gender • Ethnicity • Education • Marital Status	• Age in years • 0=Female; 1=Male • 0=Ethnic Minority (other); Ethnic Majority (Afro-Trinidadian)[3] • 1=Primary or Below; 2=High School/Secondary; 3=Technical Vocational; 4=College Tertiary • 1=Single; 2=Single but living with someone; 3=Married; 4=Separated/Divorced/Widowed
Perception of Disorder and Crime	
• Physical Disorder Index • Social Disorder Index • Crime is a Top 3 Problem in the Neighborhood • Crime is a Reason to Stay Away from Areas	• From scale measures of perceptions of physical disorder, coded, summed and divided by total number of valid questions per respondent • From scale measures of perceptions of social disorder, coded, summed and divided by total number of valid questions per respondent • 0=not named as a Top 3 problem; 1=named as a Top 3 problem • 0=Crime is not a reason to stay away; 1=Crime is a reason to stay away
Neighborhood Familiarity and Tenure	
• Neighborhood Tenure • Neighborhood Familiarity • Time Outside of Home	• Number of months resided in the community • Index from scale measures of familiarity with key landmarks coded, summed and divided by total number of valid questions per respondent • Number of days/week outside of the community

[3] Afro-Trinidadian is the ethnic majority for the study neighborhoods, and not for the country overall.

Individual Demographics

Age – Age is a continuous level variable and was measured from a question asking the respondent, "What is your age?" Respondents reported their age in years. For the sample overall, respondents ranged in age from 18 years to 73 years of age, with a mean age of 32.2 years (SD=13.22 years).

Gender – Gender is a dichotomous measure with the possible responses of male or female. The question was answered from sight by the interviewer who administered the survey and was coded 0 for Female and 1 for Male. Just over two-thirds of the sample were male (69.8%) and less than one-third were female (30.4%).

Ethnicity – Ethnicity was measured by way of a question that asked, "What is your racial/ethnic background". Respondents were given a number of categorical responses to choose from. These categorizations mimic previous research conducted in Trinidad and Tobago (see Johnson, 2007) and reflect the categorizations reported by the Trinidad and Tobago 2000 census (Central Statistical Office). The possible responses available to respondents included African/Afro-Trinidadian, East Indian/Indo-Trinidadian, Mixed, and Other. The most common reported ethnicities among survey respondents is Afro-Trinidadian (69.0%), Mixed, which is generally a combination of Afro-Trinidadian and Indo-Trinidadian (21.4%) and East Indian/Indo-Trinidadian (9.5%). No respondents from either of the two communities identified themselves as another ethnicity/race.

Since hypotheses have only been made about the majority population in the area, the categorizations were then re-coded into a binary measure representing majority and minority ethnicity/race populations in the sampled areas. Specifically, two categories were created that represent the majority ethnicity/race population, Afro-Trinidadian (61.1% in Belmont and 78.2% in Morvant) and all other responses as minorities. Thus, if a respondent reported themselves as Afro-Trinidadian, they were coded as 1 and if the reported any other ethnicity/race classification, their response was coded as 0. Once dichotomous, the sample consisted of 69.05% Afro-Trinidadian (Ethnic Majority) and 30.95% Other (Ethnic Minority).

Education – Education was measured with a question that asked respondents, "What is the highest level of formal education that you have attained?" Respondents were given seven possible categorical responses to choose from. Responses to the education question included: none, primary, junior secondary, secondary, technical/vocational, and tertiary/university. Again, this question was borrowed from previous survey work in Trinidad and Tobago (Johnson, 2007).

When asked about their highest level of education, 60.1% of respondents reported secondary (i.e., high school), 14.9% reported primary school, 11.9% reported technical/vocational school, 7.1% reported tertiary or university schooling, and 5.4% reported junior secondary. One respondent (.6%) stated they had never attended school. Since there were low response rates in some of the original categorizations, I adjusted the education measure into four new categories using the Trindad and Tobago 2000 Census: Primary or below (20.8%), High School/Secondary (60.1%), Technical/Vocational (11.9%), and College/Tertiary (7.1%).

Marital Status – Marital status is measured using a number of possible categorical responses. Specifically, respondents were asked, "What is your current marital status?" Respondents were able to choose: single, never married, living with someone, but not married, married, separated/divorced, and widowed. A majority of respondents reported they were single/never married (55.4%) while 22% stated they were single but living with someone. Only 22.7% reported being married at some time, with 13.1% stating they were currently married, 5.4% reporting they are separated or divorced, and 4.2% reporting they are widowed.

Since some of the original classifications had low response rates (responses <5), this variable was re-coded into four new classifications including: Single (55.4%), Single, but Living with Someone (22.0%), Married (13.1%), and Separated/Divorced/Widowed (9.5%).

Individual Perceptions of Disorder and Crime

To examine how people perceived crime and disorder, respondents were asked a number of questions about potential neighborhood problems. The original form of many of these questions is categorical; however, some are open-ended. Therefore, in order to use these responses in the overall model, I converted these measures into variables that represented a person's overall perception of physical disorder, social disorder, and crime in their neighborhood. In this section, I will review the summaries of the original responses, as well as the descriptive statistics of these measures once they were re-coded into continuous level measures.

Perceptions of Physical & Social Disorder Score – Respondents were first asked to report on their perceptions of physical disorder in their community. Respondents were given a series of questions that asked if different types of physical disorder, including trash and garbage on the sidewalks/street, visible graffiti, vacant or abandoned houses/buildings, poor lighting, abandoned cars, and empty or overgrown lots of land were a big problem, somewhat of a problem, or not a problem.

A breakdown of the response distribution to each of the indicators is included in Table 6.1 below. The physical disorder indicator cited as a big problem by most respondents is trash/garbage on the sidewalks/streets (48.2%). No more than 19% of respondents indicated any of the other physical disorder measures were a big problem in their community. Several issues were considered to not be a problem by a majority of the sample. Specifically, over 50% of the sample indicated abandoned cars (75.6%), poor lighting (64.9%), graffiti (60.1%), and vacant/abandoned buildings (53.6%) were not a problem in their community.

Table 6.1 – Response Distribution for Indicators of Physical Disorder

	N	**Not a Problem**	**Somewhat of a Problem**	**A Big Problem**
Trash/Garbage on Sidewalks and Streets	168	19.6%	32.1%	48.2%
Graffiti on Buildings and Walls	168	60.1%	25.0%	14.9%
Vacant/Abandoned Buildings	168	53.6%	32.7%	13.7%
Poor Lighting	168	64.9%	16.1%	19.0%
Abandoned Cars	168	75.6%	17.9%	6.5%
Empty or overgrown lots of land	167	48.5%	34.7%	16.8%

Perception of Social Disorder Score – Respondents were also asked about instances of social disorder in their neighborhood. Similar to the physical disorder measures, respondents reported on the seriousness and prevalence of specific social disorder problems in their community. Questions asked whether groups of teenagers or adults hanging out in the neighborhood, people buying and selling drugs on the street, people drunk in public/on the street, people smoking marijuana in public, loud or unruly neighbors, vagrants/homeless people, and truancy/youth skipping school, are problems in the community. Respondents were again able to report if these were a big problem, somewhat of a problem, or not a problem. The distributions of the original responses are listed in table 6.2 below.

Table 6.2 - Response Distribution for Indicators of Social Disorder

	N	Not a Problem	Somewhat of a Problem	A Big Problem
Groups of people hanging out and causing trouble	168	39.3%	29.2%	31.5%
People buying and selling drugs on the street	161	31.5%	29.0%	38.9%
People drunk in public/on the street	167	49.1%	28.7%	22.2%
People smoking marijuana in public	165	25.3%	33.3%	39.9%
Loud/unruly neighbors	168	48.2%	31.0%	20.8%
Vagrants/Homeless people	167	62.9%	16.2%	21.0%
Truancy/youth skipping school	159	49.1%	21.4%	29.6%

Perceptions of social disorder seem somewhat different from perceptions of physical disorder. Essentially, it appears that fewer respondents identified social disorder as a problem(with the exception of vagrants/homeless people). The social disorder most often cited as a big problem by respondents is people smoking marijuana in public (39.9%), with people buying and selling drugs on the street (38.9%) and groups of people hanging out and causing trouble (31.5%) ranking second and third respectively. Yet, for these same problems, similar proportions of respondents reported them to be either somewhat of a problem (33.3%, 29.0% and 29.2% respectively) or not a problem at all (25.3%, 31.5% and 39.3%). The social disorders least often cited as being a problem are vagrants/homeless people (62.9%), people drunk in public (49.1%), and truancy (49.1%).

In order to gain a sense of overall disorder perceptions, I combined each of the ordinal measures and created two new variables that contained proportional index scores. These variables were created so that a higher score represents a more negative perception of disorder and a lower score represents a less negative view of disorder in the community. In each of the original questions, responses were given a score of 2 if they considered it to be a big problem, 1 if they considered the measure to be somewhat of a problem, and 0 if they do not consider the physical disorder to be a problem. In order to make the two new scale measures, I summed the ordinal value for each of the questions to obtain an additive score and then divided by the total number of disorder questions for each phenomenon to obtain the final index.

Although these proportion scores sound good in theory, I had to be sure that combining the measures of physical and social disorder is appropriate. To check, I ran reliability analyses on the two sets of questions. The Cronbach's Alpha level for the six physical disorder measures was .674. Although this alpha is not great, removing any of the items would result in a lower Cronbach's Alpha if deleted. For the social disorder indicators, the Cronbach's Alpha was better, .837, and again removing any of the items would not result in an improved alpha level. Thus, all of these measures are needed to create the final disorder measures.

Since these measures are appropriate for inclusion, I also needed to determine whether it was possible to save cases where there was a missing response to at least one of the original questions. Upon investigation of the dataset, there was one missing response to a physical disorder question and thirteen missing responses to social disorder measures. Each of the missing cases was the result of a respondent replying that they either did not know if the indicator was a problem in their community or they simply refused to answer the question (this only happened in one instance, one respondent refused to answer whether people buying and selling drugs in their neighborhood was a problem). When the survey was created these responses were meant to be coded as missing; however, it is extremely likely that people may not know whether a certain type of disorder is occurring. For example, people go to work during the day and may not be home to witness whether or not youths are skipping school. Completely excluding these thirteen cases from the sample seemed inappropriate.

The most appropriate solution was to calculate scores for these respondents using an adjusted score variable. Essentially, this adjusted score represented each respondent's valid score divided by an adjusted denominator (i.e. number of valid questions). So, for a respondent that had 'valid' responses to the seven social disorder questions, their score was computed by summing each of the scores from each question and then dividing by the number of questions. Therefore, for a respondent who replied with do not know or refuse to a question, I only summed the scores for the 'valid' responses and then summed by a denominator that reflected those questions (i.e., if a respondent replied do not know to two of the seven questions, their overall score was then divided by five instead of seven).

Before I could deem this solution appropriate, I had to test whether there were differences between those who responded to all of the disorder questions versus those that did not. Essentially, I created two new variables - one proportion score that excluded replies of ‘do not know’ or ‘refuse’ from the sample and another of a proportion score that was calculated using only the valid questions in the denominator. To check if that approach was appropriate, I ran an independent samples t-test on the two groups (0=group with standard denominator, 1=group with adjusted denominator). The results indicate that there were no significant differences between the two groups. Thus, for the regression model, I will use the adjusted disorder scores. Physical disorder index scores range from 1 to 3 with a mean of 1.66 and a standard deviation of .447. The social disorder index has a slightly higher mean of 1.84 (range 1-3; SD=.586)

Perception of Crime – Although the survey did not include measures that asked about crime perceptions, it was still possible to gain a sense of individual perceptions of crime as a major community concern. To gain an understanding of how respondents perceived the crime problem, I examined an open-ended question asking respondents to name the top three problems in their neighborhood. This question was an open-ended question, respondents could name any possible issue they felt was a problem. Their responses were coded into a categorical measure, featuring 8 different categories. The distribution of responses is listed in Table 6.3 below. As the table indicates crime was reported as the top problem for the respondent’s first possible response and was the second most mentioned for the #2 problem named (45.8%). Table 6.3 also shows that crime issues were most commonly mentioned in response to the top problem in the community (45.8%), followed by infrastructure (29.8%), Unemployment (6.5%), and Police Misbehavior (4.8%). For the second biggest problem, crime ranks second (21.4%), following problems with infrastructure (35.2%). Also worth noting is how consistently problems with infrastructure were named across all three problems, and how no identified problems increased from problem #1 (0.6%) to problems #2 (7.7%) and #3 (28.6%).

Table 6.3 – Common Responses to Biggest Problems in the Community

	Biggest Problem #1	**Biggest Problem #2**	**Biggest Problem #3**
Crime	45.8%	21.4%	5.4%
Infrastructure	29.8%	35.2%	31.6%
Physical or Social Disorder	3.0%	5.4%	9.5%
Police Misbehavior	4.8%	6.6%	4.8%
Lack of Community Facilities	4.2%	10.7%	5.7%
Unemployment	6.5%	5.4%	6.0%
Fear, Concerns about Safety	1.8%	3.0%	1.2%
Other	3.6%	4.2%	7.7%
No Identified Problem	0.6%	7.7%	28.6%

Interestingly, when I make this variable dichotomous (i.e., 0=crime is not mentioned in any of the Top 3 responses; 1=crime is mentioned in any of the Top 3 responses) just a little over half (57.1%) of respondents consider crime to be a neighborhood problem at all. This dichotomous measure is one of the perceptions of crime variables that I will use in the analysis models.

In a second attempt to get at perceptions of crime, I recoded a question which asked respondents about why they would avoid the areas they marked into a dichotomous measure of perception of crime. Respondents who mentioned concerns about specific crimes (i.e., robbery, shooting, molestation, rape, killing, gang warfare, and drugs) and those who reported crime in general were scored as 1. Respondents who did not mention a crime issue were given a 0[4]. All in all, of the 161 valid responses, 70.8% cited a crime issue and 28.0% did not.

After running a correlation test on the two perceptions of crime responses, it appears the two variables do not represent the same phenomenon. Specifically, the correlation test revealed a non-significant Pearson's Correlation of -.035. I suspect that this is because the two questions ask very different things. For instance, respondents may not consider crime to be one of the top three problems in the larger neighborhood but instead isolated in very specific areas. Indeed, respondents may associate the threat of crime and victimization to very small pockets within a larger geography, supporting empirical findings of the concentrations and stability of crime. Consequently, both measures will be included in the analysis models.

Neighborhood Familiarity and Tenure

The third set of independent variables that will be included in the regression analyses are those that relate to a respondent's neighborhood tenure and familiarity. These questions help diagnose the length of time a respondent has lived in a community

[4] Although gangs and gang activity can be considered criminal, it was not coded as a crime unless there was a mention of warfare, gun violence, or other specific crime problem. Additionally, in many instances, respondents' replies concerned issues of danger and safety; however, unless a crime issue was also mentioned, these were coded as 0.

and whether their familiarity with the community influences their ability to identify problem crime locations.

Number of Months in the Community & in Current Residence– Number of Months in the Community is a continuous level variable. The data for this variable corresponds with the question "How long have you lived in your community?" The responses were gathered for both years and months. Years were then calculated into months so that the total number of months could be obtained.

Time in Residence is a continuous level measure of the number of months that a respondent has lived in their current residence. Respondents were specifically asked "How long have you lived at your present address?" Like the number of months in community measure, responses were reported in both years and months. For analysis purposes, all reported years were converted into months (by multiplying by 12).

On average respondents reported they have lived within their community 257.19 months and have lived at their current address approximately 224.20 months. Although there is some difference in the measure, these questions are significantly, positively correlated (R2=.849, p=.000). Thus, the measure of how long they have lived at the current address will be dropped. This was done because tenure in the community is essentially a better measure of their overall time spent in the neighborhood.

Neighborhood Familiarity Score – The Familiarity Score variable is a proportional index score calculated from responses to nineteen separate questions that inquired about familiarity with identified landmarks in the community. Specifically, respondents were asked if they were very familiar, familiar, not familiar or very unfamiliar with each landmark. Respondents were then given scores that ranged between 1 and 4, 4 meaning they were very familiar and 1 meaning they were very unfamiliar. The landmarks that were included in the survey included schools, churches, car dealerships, police stations, and medical facilities[5]. The responses for each of the nineteen questions were summed for each respondent in order to gain a continuous measure of familiarity for each respondent. The neighborhood familiarity score is the sum of respondents' replies to each familiarity question divided by the number of familiarity questions. Summed scores ranged from a minimum of 1.44 to 4.00, with a mean of 3.20 (SD=.641).

Time Outside of Home – To measure time outside of the home respondents were asked "How many days per week do you leave your community for work, shopping, socializing, etc?" Respondents were asked about the number of days (versus hours) in hopes of getting a better approximation of time spent away from the community. Responses ranged for 0 (no days outside of the home) to 7 (every day outside of the home). On average, respondents left the community 5.28 days of the week (range=0-7, SD=1.82).

Additional Variables

In designing this study it became apparent that there needed to be some sort of measure that could control for the percentage of the entire map that respondents marked.

[5] The locations used in the familiarity portion of the survey were the same landmarks that were used in the cognitive mapping exercise later in the survey. The cognitive maps included these labeled landmarks, along with labeled streets, as a way for the respondents to orient themselves with the map.

For instance, initial review of the maps suggested some respondents appeared to have really taken the time to pick apart specific areas and locations while others marked the entire area of the map. Therefore, I include two different control measures that assess the proportion of the map that was marked during each exercise: Percent Marked Day (which is the marked area/total area*100) and Percent Marked Night (marked area night/total area*100). For both measures, the range was 0% to 100%. Percent Marked Day had a mean of 6.31% (SD 14.40%). The mean of Percent Marked Night was 9.39% (SD 16.43%). Both measures also had high skewness and kurtosis statistics. The Percent Marked Day had a skewness statistic of 4.26 and a kurtosis of 23.34. Percent Marked Night was a little better (skewness 3.23; kurtosis 15.31); however, neither measure is indicative of a normal distribution. Moreover, these descriptive statistics indicate that respondents marked more area (higher mean and standard deviation, lower skewness and kurtosis) for the night question than they did for the day question. To give a better sense of the distribution, 50% of the sample marked less than 1% the of day map (0.93%). Likewise, for the Night Map exercise, 50% of the study sample marked 2.42% or less of the map. Histograms of both measures are included in Appendix C.

Analysis Technique

Initially, I planned to use multivariate regression as the primary analysis technique for this study. However, based on the diagnostics on the dependent variables, a standard multivariate regression analysis is no longer appropriate. Based on the format of and descriptive diagnostics of the hot spot dependent variables, the most appropriate model to use is a regression that allows for count outcomes that account for inflated zeros. These conditions lead to two possible analytic techniques - Zero-Inflated Poisson and Zero-Inflated Negative Binomial analyses. According to Long & Freese (2006), zero inflated models allow for a change in the mean-variance relationship (in Poisson Regression Model it assumed that the mean equals the variance; in negative binomial regression the variance can be larger than the mean). To allow for this change, the zero-inflated models assume that 0 counts can be the result of a independent process than what is tested in the model. In essence, two models are run simultaneously, one that tests the hypothesized effects and one that tests whether certain predictors can explain inflated zero count outcomes independently.

Since the crime cool spots are not inflated at 0, but instead are skewed at the end of the distribution, the zero-inflated count models are not a good a fit. In order to make the analysis of these measures simplistic, I will convert the reversed cool spot accuracy scores into five categorizations ranging from least accurate to most accurate in order to run an ordinal logistic regression analysis. I detail this process further the next chapter.

Conclusion

Overall, the second goal of this study is to examine the influence of a number of key factors related to individual demographics, perceptions of disorder and crime, and neighborhood familiarity on respondents' abilities to accurately identify crime and non-crime locations in their neighborhood. To examine this relationship, I will use two types of regression analysis. Specifically, I will use the appropriate count regression model that allows for zero-inflated variables for the general crime and violent crime hot spot models. For the crime cool spots, I will use ordinal logistic regression analysis. I present and discuss these results in the next chapter.

CHAPTER 7: RESULTS

In this chapter, I present the predictive analysis results. Recall that the second goal of this study is to examine what factors influence the accuracy with which people can identify hot and cool crime locations in their perceptions of unsafe/dangerous areas within their own neighborhoods. Specifically, I am testing how individual demographics, perceptions of disorder and crime, and neighborhood familiarity and tenure influence a respondent's ability to accurately include select crime and non-crime places in their cognitive maps of unsafe/dangerous areas. Detailed information about the study data is in Chapter Four and details about each of the variables in the following models are contained in Chapters Five and Six.

Day and Night Differences

One proposed hypotheses is that there is a significant difference in the areas that respondents marked as unsafe/dangerous during the day and those that they marked for night. This first question is important to address since the area that respondents marked for each of the questions (day and night) is the control measure for each of the predictive models. A difference would also indicate that respondents are interpreting the areas they consider unsafe/dangerous differently for the two time periods, which is an argument often cited in fear of crime literature. Specifically, many fear of crime scholars contend that fear responses to crime and danger are often mediated by the time of day (see Garafalo, 1981; Skogan, 1990).

To test for any differences between the areas respondents marked for both periods, I ran a paired t-test of the two measures, which tested if perceptions of problem areas at night are bigger than the problem areas marked for the day by respondents. The results of this analysis are included in Table 7.1 below.

Table 7.1 Paired T-Test for Percent Day versus Percent Night

		Paired Differences							
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	T	df	Sig. (2-tailed)
Pair 1	PerMapDay - PerMapNight	-3.08421	7.16765	.57204	-4.21416	-1.95427	-5.392	156	.000

As Table 7.1 illustrates, the two measures are significantly different, yet they have a very high positive statistical correlation. The paired samples t-test indicates that respondents drew significantly larger areas (p=.000), marking, on average, more area for the night question (mean=9.39%) than for the day question (mean=6.31%). Moreover, there is a strong significant correlation between the two measures (R=.900). This indicates that the day and night areas that respondents marked larger for the night than the day.

Overall, these results have three implications for this research. First, although similar, there are significant differences in the proportion of the map that respondents marked for the day and night questions. Moreover, these results confirm the earlier finding that respondents are more accurate at encompassing hot spots in their perceptions of dangerous/unsafe areas at night than they are with their perceptions of these locations during the day. A second implication of these results is that they confirm earlier suspicions that cool spots may be a product of the area marked by respondents and not necessarily a good measure of a person's knowledge or ability to decipher between crime hot spot and crime cool spot locations. This finding supports what the fear of crime literature often presumes in that respondents tend to widen the criteria for unsafe/dangerous areas dependent on the time of day.

The third conclusion is more technical and it is simply that two separate control measures will need to be used in the predictive analyses. Specifically, because significant differences exist in the areas marked and in the accuracy score for the times of day, the appropriate measure needs to be included in each model in order to properly control for any effects that are explainable from the size of the areas people mark.

Analyses

The next round of analysis is to test the influence of the hypothesized predictors on each of the six dependent variables. Before moving forward with the zero-inflated count regressions, I ran model fit diagnostics on each model. This process helped determine the most appropriate technique for each of the four hot spot variables. Specifically, I ran a correlations matrix, VIF, and tolerance statistics on the independent variables to ensure that there was no multicollinearity among the measures (see Appendix F). The results indicate that there were no problems with multicollinearity. Specifically, no correlation is above .54 (between physical and social disorder), no VIF statistic is over

2.02 (Gujarati (2003) cites the standard threshold is 10.0) and the all of the tolerance statistics are above .20 (see Weisburd & Britt, 2004, p. 516.). In order to determine the appropriate zero-inflated technique, I also ran different model fit analyses using the countfit and prcounts commands in Stata developed by Long and Freese (2006). The results of each of these model fit test are also included in Appendix G[6].

I should note that for three of the four dependent measures that represented counts for day responses (hot day and cool day), the ln alphas were so large that the countfit and prcounts could not compute predicted alphas. In researching this issue, I came across a disclaimer from Long and Freese (2001) that states,

> In negative binomial regression or zero-inflated negative binomial regression, the estimate of ln alpha can be so large and negative that Stata does not return an estimate for alpha. Instead, a missing value (.) is returned. The formula for calculating the predicted probabilities in these models includes alpha, and so these probabilities cannot be computed if no value for alpha is returned. In these situations, you may wish to consider estimating the model with Poisson or zero-inflated Poisson instead.
> (Retrieved from:
> http://www.indiana.edu/~jslsoc/web_spost/spfaq_pralphaerror.htm)

Therefore, for these three dependent measures, I ran the countfit and prcounts analyses using just Poisson, Negative Binomial, and Zero-Inflated Poisson models. Unless otherwise noted, the default analysis technique I used was Zero-Inflated Poisson[7].

[6] Although the technique of diagnosing the appropriate model with prcounts and countfit statistics is common in zero-inflated count regression cases, others argue that post-model selection is problematic in that in can compromise statistical tests and confidence intervals (Berk, Brown, & Zhao, 2010). Again, the results here need to be viewed as exploratory and with considerable caution.

[7] Although not included in these models, a separate analysis was run using a question that inquired about fear of crime when walking through the neighborhood alone, during both the day and night. The results confirmed that these fear measures were not statistically significant, nor did they ultimately change the outcomes of the models presented.

Lastly, I report results at different significance thresholds for each of the outputs. Traditional thresholds of .05 and .001 are used, but I also report findings that reached or approached significance at the .10 level. This was done because this study is exploratory in nature and the goal is to understand not only what predictors are noteworthy but to also understand trends across the models. Yet, the use of this lowered threshold allows for a greater possibility that the discovered effects are from chance instead of an actual inferential effect. Therefore, these results need to be viewed with considerable caution.

General Crime Hot Spots

For the first set of analyses, I examined how the hypothesized predictors influenced whether general crime hot spots were included in respondents' perceptions of unsafe/dangerous areas for both the day and the night. To obtain these results, I ran two separate sets of analyses. First, I ran a Zero-Inflated Poisson regression analyses to understand day accuracy. Next, I ran a Zero-Inflated Negative Binomial model to understand night accuracy. The result of each analysis is listed in Table 7.2 below.

Table 7.2 – Regression Results for General Crime Hot Spots

	Hot Spot Day			Hot Spot Night†		
	Coeff. (p)	**SE**	**e^b**	**Coeff. (p)**	**SE**	**e^b**
N	152			152		
Log-Likelihood	-158.4132			-206.1694		
LRchi2(13)	96.51			75.40		
Prob > chi2	0.000			0.000		
Demographics						
Age	.0217875 (0.091)*	.013	1.02	.0041507 (0.674)	.010	1.00
Gender	-.5227341 (0.022)**	.229	0.59	-.399501 (0.025)**	.179	0.67
Ethnicity	.1039969 (0.644)	.225	1.11	.0920355 (0.614)	.182	1.10
Education	.1883656 (0.081)*	.108	1.21	.0472385 (0.632)	.099	1.05
Marital Status	-.0641444 (0.630)	.133	0.94	0.83297 (0.418)	.103	1.09
Crime – Top 3 Neighborhood Problem	.000916 (0.996)	.189	1.00	.2864928 (0.113)	.181	1.33
Crime – Reason to Avoid Marked Areas	.1648197 (0.429)	.208	1.18	-.055698 (0.743)	.170	0.95
Perception of Physical Disorder	0.121352 (0.957)	.223	1.01	.0495043 (0.799)	.195	1.05
Perception of Social Disorder	.3550512 (0.115)	.226	1.43	.1404348 (0.455)	.188	1.15
Length of Neighborhood Residency	-.0014733 (0.046)**	.001	0.99	-.0003029 (0.599)	.001	0.99
Neighborhood Familiarity Score	.5659694 (0.002)**	.182	1.76	.432635 (0.001)***	.134	1.54
Time Outside of the Community (days/week)	-.0492508 (0.311)	.049	0.95	-.0260754 (.0535)	.042	0.97
Percentage of Day Map Marked	0.301148 (0.000)***	.003	1.03	- -	- -	- -
Percentage of Night Map Marked	- -	- -	- -	.0287831 (0.000)***	.003	1.03
Constant	-2.313688 (0.026)**	1.04	- -	-.1472322 (0.091)*	.872	- -

*p=.01
**p=.05
***p=.001
† Model run using Zero Inflated Negative Binomial

General Crime Hot Spots - Day

From this output we can see that four variables, including gender, length of neighborhood residency, neighborhood familiarity and the control – percentage of day map marked, are statistically significant predictors of hot spot accuracy scores during the day. According to these results, when holding all other variables constant, being a female respondent increases the likelihood of accurately identifying hot spots during the day. In fact, the likelihood of men accurately identifying general crime hot spots is 41% lower than women. This suggests that men are almost half as likely as women to accurately identify general crime hot spots.

These results further suggests that the length of neighborhood residency is also a significant predictor (p=0.046), but not in the hypothesized direction. Essentially the Zero-Inflated Poisson regression results indicate that an additional month of residency in the neighborhood decreases the likelihood of general crime hot spot accuracy by 0.1%, when holding all else constant.

Neighborhood familiarity is also a significant predictor of general crime hot spot accuracy (p=0.002) and in the hypothesized direction. According to these results, when controlling for all other variables, a one-point increase in neighborhood familiarity increases the likelihood of general crime hot spot accuracy by 76.1%.

The last statistically significant predictor is the control variable, percentage of day map marked. This predictor is highly significant (p=0.000) and again is in the expected direction, indicating that those who marked more of the map are more likely to accurately identify crime locations in their cognitive map of crime hot spots. Essentially, for a 1%

increase in the percentage of the day map marked, the likelihood of general crime hot spot accuracy increases by 3.1%, when controlling for all other variables.

Although not significant at the traditional threshold of p=0.05, two additional variables, age and education, were significant at the 0.10 level and social disorder approached significance at this lowered threshold (p=.115). These results are noteworthy only because the study sample size is so small (N=152) and the model is so complex (13 independent variables). Contrary to the hypothesized relationship, for a one-year increase in age, the likelihood of general crime hot spot accuracy improves by 2.2%, when holding all other variables constant. Additionally, these results suggest that, when holding all else constant, a one-unit increase in education classification increases the likelihood of general crime hot spot accuracy score by 20.7%. This is in-line with the hypothesized relationship presented in Chapter Three. Finally, perception of social disorder follows the hypothesized statement that residents who have higher perceptions of social disorder are more likely to identify general crime hot spots in their maps of dangerous/unsafe areas in the neighborhood. Specifically, for a one-point increase in the social disorder perception score, the likelihood of general crime hot spot accuracy score increases by 42.6%, when holding all other variables constant.

General Crime Hot Spots - Night

For the hot spot night model, three predictors, gender, familiarity score and percentage of map marked, reached significance at the .05 level. Like the results for the general crime day model, respondents who are women, who have higher neighborhood familiarity, and who marked larger portions of the map are more likely to accurately identify general crime hot spots in their cognitive maps of unsafe/dangerous areas. This effect is very similar to that of the results from the general crime day model. The likelihood of men identifying general crime hot spots at night is 33% lower than women, when controlling for all other variables.

According to the general crime night model results in Table 7.2, respondents who are more familiar with their neighborhood are more likely to have improved general crime hot spot accuracy. Essentially a one-point increase in neighborhood familiarity score increases the likelihood of general hot spot night accuracy at night by 54.1%. Again, this finding is in line with the predicted relationship and with the findings from the general crime day model. Although, it is worth noting that the percent change is smaller for the general crime night responses. The time of day may might have an influence (i.e., respondents who can identify problem areas during the day have a better understanding), making the effect smaller for the night. Another explanation of the time of day influence could be that some respondents consider certain crime hot spots safe during the day, but not at night.

As expected, the percentage of the night map that respondents marked is a significant predictor of the inclusion of crime hot spots in the respondents' cognitive maps of problematic places. For a 1% increase in the percentage marked, the likelihood of general hot spot accuracy identification at night increases by 2.9%, when holding all other variables constant. The significance, standard error, and coefficients for the general crime day and night maps are very similar.

One other predictor, crime as a top three problem in the neighborhood, approached the higher .10 significance level (p=0.113). These results indicate that, when holding all else constant, respondents who reported crime as one of the Top 3 neighborhood problems have a 33.2% increase in the likelihood of general crime hot spot night accuracy over those that do not report crime as a top three neighborhood problem.

Overall, from the general crime models, we can see that three variables, gender, neighborhood familiarity, and percentage of map marked, seem to be significant predictors of hot spot inclusion in locations that are considered unsafe or dangerous. Two of these relationships are in the predicted direction. Specifically, I hypothesized respondents who were more familiar with their neighborhood and those who marked a larger percentage of the cognitive map would have better hot spot identification accuracy. The gender/accuracy relationship is however, in the opposite direction of what I predicted with the initial hypotheses.

Violent Crime Hot Spot Results

The second set of models examines the influence of the study predictors on violent crime hot spot accuracy of respondents. Again, I ran two sets of analyses, one for accuracy of identifying violent crime hot spots during the day and the other for accuracy of identifying violent crime hot spots during the night. This was done because of the improved distribution of accuracy scores for the dependent measure when only violent crimes were included (see Chapter 5 for more detail). Both models required the use of

Zero-Inflated Poisson regression (see Appendix G for the model fit diagnostics). The results of each of these models are included in Table 7.3 below.

Table 7.3 – Regression Results for Violent Crime Hot Spots

	Hot Spot Day			Hot Spot Night		
	Coeff. (p)	**SE**	**e^b**	**Coeff. (p)**	**SE**	**e^b**
N	152			152		
Log-Liklihood	-162.5048			-205.6061		
LRchi2(13)	99.98			127.43		
Prob > chi2	0.000			0.000		
Demographics						
Age	.0085263 (0.475)	0.012	1.01	.0026954 (0.777)	.010	1.00
Gender	-.3197273 (0.135)	0.214	0.73	-.4263294 (0.015)**	.174	0.65
Ethnicity	.1256593 (0.550)	0.210	1.13	.018904 (0.908)	.163	1.02
Education	.0030163 (0.979)	0.116	1.00	-.0460627 (0.617)	.092	0.96
Marital Status	-.0017787 (0.988)	0.120	1.00	.1726222 (0.064)*	.093	1.19
Crime – Top 3 Neighborhood Problem	-.104333 (0.560)	0.179	0.90	0.125316 (0.419)	.155	1.02
Crime – Reason to Avoid Marked Areas	.2593014 (0.190)	0.198	1.30	0.023828 (0.878)	.155	1.13
Perception of Physical Disorder	-.0465801 (0.815)	0.199	0.95	0.065508 (0.712)	.177	1.07
Perception of Social Disorder	.402253 (0.045)**	0.201	1.50	0.2560316 (0.138)	.173	1.29
Length of Neighborhood Residency	-.0003208 (0.666)	0.001	1.00	0.0001879 (0.732)	.001	1.00
Neighborhood Familiarity Score	.480244 (0.003)**	0.164	1.62	0.3514692 (0.003)**	.118	1.42
Time Outside of the Community (days/week)	-.0106467 (0.816)	0.458	0.99	-.0157728 (0.684)	.039	0.98
Percentage of Day Map Marked	.0277046 (0.000)***	0.003	1.03	- -	-	-
Percentage of Night Map Marked	- -	-	-	0.0257984 (0.000)***	.002	1.03
Constant	-1.982422 (0.045)**	0.990	-	-1.145703 (0.146)	.787	-

*p=.01
**p=.05
***p= .001

Violent Crime Day Hot Spots

For the violent crime day hot spot model, three variables were significant, neighborhood familiarity, percentage of map marked, and perception of social disorder score. Like the day models, the neighborhood familiarity and the percentage of map marked were both highly significant and in the expected direction. For a one-point increase in the neighborhood familiarity measure, the likelihood of violent crime hot spot identification during the day increases by 61.6%. Likewise, for a 1% increase in the percentage of the map a respondent marked, the violent crime hot spot day accuracy score increases by a likelihood of 2.8%, when holding all else constant.

A new variable of interest, which only approached significance in the general crime night model, is the social disorder perception score of respondents. In the violent crime hot spot day model, this predictor is significant and the coefficient is in the expected direction. Essentially, those that had higher perceptions of social disorder are more likely to identify violent crime hot spots on their day map. For each one-point increase in the social disorder perception score, the violent crime hot spot accuracy score increases by a likelihood of 49.5%. This finding supports the study hypothesis that higher perceptions of social disorder lead to a better ability to predict crime hot spots. Even though this measure is not significant for the night, it does come close (p=.138) to the lower .10 threshold and the coefficient is in the expected direction.

Although not significant at .10, the gender coefficient for the violent crime day hot spot model is noteworthy. As with the general crime models, women are more likely to identify crime hot spots than men. Results suggest that men are almost 30% less likely to accurately identify violent crime hot spots during the day than women, when holding all else constant.

Violent Crime Night Hot Spots

Three variables reached significance in the violent crime night hot spots model: gender, neighborhood familiarity, and percent map marked. Like the general crime hot spot day and night models and the violent crime hot spot day model, the findings for gender indicate that women are more likely to include crime hot spots in the areas that they mark as unsafe or dangerous. Specifically, women are 34.7% more likely than men to accurately identify violent crime hot spots at night, when holding all else constant.

Also following the trends of past models, the violent crime hot spot night results indicate that residents who have higher neighborhood familiarity scores are more likely to identify violent crime hot spots in the areas they consider unsafe or dangerous at night. Based on the results, when controlling for all other predictors, a one-point increase in familiarity score increases the accuracy of violent crime hot spots identification at night by a likelihood of 43.0%.

Again, as expected the control variable, percent of map that was marked is a significant predictor of the inclusion of crime hot spots in areas considered dangerous or unsafe by respondents. The results indicate that, when holding all else constant, for a 1% increase in the percentage of map marked, the likelihood of hot spot identification increases by 2.6%.

Two variables reached or approached significance at the lowered threshold of .10. Marital status reached significance indicating that respondents who are or have been married are better at identifying crime hot spots in their maps of dangerous or unsafe places. Specifically, the results indicate that for a one-category increase in marital status the likelihood of accurately identifying violent crime hot spots with perceptions of dangerous or unsafe areas increases by 18.8%. This finding supports the original study hypothesis that respondents who are or have been married are better at identifying crime hot spots in their community.

Additionally, perception of social disorder approached but did not reach significance at the lowered threshold (p=.138). The results indicate that for a one-point increase in perception of social disorder score, the accuracy score increases by a likelihood of 29.2%. Like the violent crime day finding, this suggests that people who have higher perceptions of social disorder are more likely to include crime hot spots in their cognitive maps of dangerous and unsafe areas.

It is worth noting for the general and violent crime models, several variables I hypothesized as significant predictors are not. Specifically, age, ethnicity, crime as a reason to avoid the area marked, perceptions of physical disorder, length of neighborhood residency, and the number of days traveling in and out of the community do not seem to have a significant influence on whether a respondent includes crime hot spots in their cognitive maps of unsafe or dangerous locations throughout the community.

Crime Cool Spot Results

In addition to examining the accuracy of identifying crime hot spots, both general and violent, I tested how well respondents were at not including 10 randomly selected cool crime spots throughout the neighborhood in their cognitive maps of dangerous areas. As the preliminary findings in Chapter Five suggests, respondents did a very good job at not including the randomly selected crime cool spots, both during the day and the night, in the areas they marked as unsafe or dangerous. However, these measures of cool spot accuracy have limitations, which I also discuss in Chapter Five. Consequently, the findings from the models below are potentially limited in that much of the cool spot accuracy is possibly explainable by chance occurrence. Regardless, these models were run to see if any individual level factors affect these measures.

Initially, because of the way this variable was calculated, the score values were misleading. Respondents who scored a 0 were actually the most accurate because they did not include any of the cool spot locations in their cognitive maps. On the other hand, respondents who scored a 10 were completely inaccurate and included all 10 randomly selected cool spots in their defined problem areas. As I explained earlier in chapter five, I reverse coded this measure so that the numbers would be more intuitive and meaningful when analyzed. Consequently, the zero-inflated count models were no longer the best analysis approach.

Therefore, in order to understand the influence of the hypothesized predictors on whether crime cool spots were included in dangerous/unsafe areas, I used ordinal logistic regression analysis. I essentially reverse coded the original scoring scale and then recoded the measures into a new variable ranging from 1-5, with each category representing the same interval among the original responses (see Appendix C for a breakdown of the new distribution). The results from these analyses are included in Table 7.4 below.

Table 7.4 – Regression Results for Crime Cool Spot Accuracy

	Cool Spot Day			**Cool Spot Night**		
	Coeff. (p)	**SE**	**e^b**	**Coeff. (p)**	**SE**	**e^b**
N	152			152		
Pseudo R2	0.5853			0.4006		
Log-Liklihood	-44.219576			-87.516387		
Prob > chi2	0.000			0.000		
Demographics						
Age	-.0065384 (0.847)	.034	0.99	-.0087106 (0.733)	.025	0.99
Gender	-.2213688 (0.759)	.723	0.80	-.064797 (0.898)	.504	0.94
Ethnicity	.2846894 (0.695)	.726	1.32	-.382535 (0.427)	.481	0.68
Education	.2189358 (0.573)	.388	1.24	.0877811 (0.760)	.287	1.09
Marital Status	-.2340185 (0.536)	.378	0.79	.0703261 (0.810)	.292	1.07
Crime – Top 3 Neighborhood Problem	-.5509149 (0.431)	.700	0.57	-.5895351 (0.229)	.490	0.55
Crime – Reason to Avoid Marked Areas	.3389843 (0.634)	.711	1.40	-.2474033 (0.656)	.556	0.78
Perception of Physical Disorder	-1.275212 (0.109)	.795	0.28	-.9566168 (0.091)*	.566	0.38
Perception of Social Disorder	.848632 (0.228)	.704	2.34	.582052 (0.234)	.489	1.79
Length of Neighborhood Residency	.0007068 (0.746)	.002	1.00	.0004793 (0.772)	.002	1.00
Neighborhood Familiarity Score	.1700515 (0.720)	.474	1.19	.2226554 (0.504)	.333	1.25
Time Outside of the Community (days/week)	.0554963 (0.731)	.161	1.06	-.0362591 (0.765)	.121	0.96
Percentage of Day Map Marked	-.3552893 (0.000)***	.062	0.70	- -	-	-
Percentage of Night Map Marked	- -	-	-	-.1923624 (0.000)***	.028	0.83

*p=.01
**p= .05
***p=.001

Cool Spot Day Results

From these results, we can see that both models are significant, with both models having over 40% of the variance explained (day cool spot R^2= .585; night cool spot R2=.4006). From, the Pseudo R^2 and log-likelihood statistics, we can see that the day model is the better fitting model. Based on the results of the two models, it appears that the influence of independent variables seem to be much different for accuracy in identifying crime cool spots with cognitive map of dangerous/unsafe areas. This is somewhat surprising considering the prior evidence that these cool spots may be a by-product of the size of areas that respondents marked on the cognitive maps. As expected the control, percent of the day and night map marked, is significant for both cool spot models. According to the results, for a one percent increase in the area of the map marked, we can expect a 30% decline in likelihood of cool spot accuracy, when holding all else constant.

In contrast to the four hot spot models, no one variable reached significance in the cool spot day model and the only predictor that approached significance was physical disorder (p=.109). Specifically, for a one-point increase in physical disorder perception score, the likelihood of cool spot accuracy decreases by 72.1%. Essentially, respondents who have lower physical disorder perceptions scores (i.e., they do not report physical disorder to be as much of a problem) are better at accurately identifying crime cool spots in areas that consider to be safe. Again, we see that the influence of social disorder and physical disorder are not the same and the coefficients are in different directions.

Cool Spot Night Results

For the cool spot night model, we can see that, the same two variables are the most significant predictors. In this model, perception of physical disorder actually reached significance at the .10 threshold (p=0.091). The results indicate that for a one-point increase in perceptions of physical disorder, the likelihood of cool spot night accuracy decreases by 61.6%, after holding all else constant. Again, the direction of this relationship indicates that respondents who have a better perception of physical disorder in their neighborhood are less likely to include any of the randomly selected crime cool spots in their perceptions of dangerous or unsafe areas at night.

As with all of the other models in this study, the percentage of the map that respondents marked as dangerous or unsafe was a significant predictor of their accuracy score for cool crime spots at night. Essentially, for a one percent increase in the area marked on the map, the likelihood of the ability of respondents to accurately identify the selected cool crime location decreases by 17.5%. Again, this indicates that the more area a respondent marks lessens their accuracy in cool spot identification.

Conclusions

From all four hot spot regression outputs, there are a few meaningful findings. First, the control variable, percent map marked, is a significant predictor of whether crime hot spots are included in a person's identification of unsafe/dangerous areas in the neighborhood. More importantly, is the finding that neighborhood familiarity score is a highly significant predictor for ability to identify crime hot spots within the neighborhood. This finding is consistent with what I hypothesized from the literature. Essentially, all four models suggest that the better a person knows their neighborhood the better able they are at identifying crime hot spots in their maps of unsafe areas for both the day and the night. It is likely that respondents who have a more nuanced understanding of the area are better able to decipher crime locations than those who are less familiar. I should also mention that the coefficients for neighborhood familiarity are slightly higher for the day versus the night. This slight difference might simply be an illustration of how the time of day changes the influence of different predictors.

In addition, in this study I find that gender is significant or approaches significance in all four of the hot spot models. Each model illustrated that gender is a likely predictor of the accuracy of including hot spots in problem locations. However, this relationship, in each of the models, was not in the expected direction. Specifically, the results suggest that women are more substantially more likely to include crime hot spots in their marking of dangerous/unsafe areas, regardless of the crime type or the time of day examined. I should note that this effect is not due to a difference in the size of the area marked by men and women. An independent samples t-test indicates there is no significant difference between men and women for the size of the area they marked on the maps (percent day, $t= -0.5034$, $p=0.6154$; percent night, $t= -0.8401$, $p=0.4022$).

Instead, a more likely explanation is that findings related to gender (all hot spot models) and length of residency (see general crime hot spot day model) possibly interact with fear. Essentially these are showing as significant because respondents with these characteristics are not necessarily different in their abilities to identify crime locations, but instead their perceptions about dangerous places encompass these places because these respondents believe they are a more vulnerable population that is at a higher risk of victimization. It is very likely that residents who are male or who have lived in the neighborhood longer are less afraid of crime hot spots because of desensitization. For instance, it is possible that male respondents believe they will not be a victim of the problems in these locations or they may not feel the need to develop this awareness because they do not consider themselves to be within the vulnerable population. If this is the case, this leads to a question about what the dependent variables in this study really measure. It is possible that the perceptions of these problem locations are driven by fear, and not necessarily by knowledge about crime. If so, equating perceptions of danger to perceptions of crime can potentially be problematic. I will visit this issue and possible limitations in more detail in the next chapter.

Furthermore, these findings preliminarily suggest that social disorder can significantly influence a respondent's perception of areas that are unsafe or dangerous. This supports what much of the literature has concluded about the effects of disorder on resident fears (Skogan & Maxfield, 1981; Wikstrom & Domen, 2001) and travel patterns (Nasar & Fisher, 1993). Interestingly, although social disorder is significant in this model, perceptions of physical disorder are not. There are a number of reasons why this may be. For one, although it is argued that in the United States physical and social disorder are correlated and often measure the same concept, the two phenomena may act differently in an international, developing democracy. Consider the neighborhoods that were surveyed are some of the poorest in the nation of Trinidad and Tobago and have high instances of disorder, some even resulting from issues with basic government infrastructure (i.e., roads make it difficult for trash pick-up). Consequently, what is considered disorderly, and to what extent, may be very different in Trinidad and Tobago than in other countries.

Another possible explanation for this difference is supported by Yang (2008). Essentially, that study found that social disorder has a different relationship with violent crime than physical disorder. Overall Yang (2008) concluded crime blocks that were in high crime trajectories were located in areas that had high social disorder. Yet places high in just physical disorder did not have this same connection. Thus, this model may be detecting a specific relationship between social disorder and violent crime hot spot locations.

The trends for crime cool spots seem to be much different. This study found that positive perceptions of the physical environment may have an impact on the ability of respondents to accurately decipher between crime hot and cool spots throughout their community, although this relationship was significant only at the .10 level and I have voiced concerns about the measurement validity of this construct. I discuss these potential limitations thoroughly in the next chapter. However, this result is worth mentioning.

It is also worth noting that age, ethnicity, education, crime as a problem in location marked, length of residency, and time outside of the community are not significant in any of the models. However, many of the coefficients are in the expected direction. The non-significant findings for the hypothesized effect of these variables should be taken with some caution considering the sample size and model complexity used in this study. Regardless, the results here indicate that these predictors do not have a real effect on whether a respondent includes crime hot or cool spots in their perceptions of dangerous or unsafe areas.

Finally, it is worth mentioning that the predictors measuring whether crime was a reason to avoid the marked areas is not a significant predictor. Again, this finding may be the result of methodology and sample size, or it could be that perceptions of crime for a particular area do not really inform respondents' opinions of a place as safe. Other issues might be a better predictor of whether locations are associated with fear. For instance, issues like the threat of victimization, which may not necessarily be criminal, might inform perceptions more than actual crime. This is conceivable if a respondent feels that they would be the target of violence that does not otherwise occur. It is also likely that this finding is the result of under-reporting of crime to the police. Many studies suggest that respondents from under-privileged areas do not report instance of crime and victimization as often to formal authorities (Sampson & Bartusch, 1998; Goudriaan, Wittebrood, & Nieuwbeerta, 2006). Much of what TTPS team members learned throughout research in Trinidad and Tobago is that this is likely true for the two areas of study as well. As with other research, if true, this could really affect the validity of police records and their representation of crime in these locations.

All in all these results suggest the factors related to gender and neighborhood familiarity influence whether respondents include both general and violent crime hot spots in their cognitive maps of unsafe areas within their neighborhood. Additionally, perceptions of social disorder seem to have a substantial impact on whether violent crime hot spots are included in perceptions of problematic areas. Yet for crime cool spots the results are quite different. Other than the control variable, the only predictor found to have any sort of an impact was physical disorder and even that result has to be viewed with extreme caution.

In the next and final chapter, I will briefly review the above findings in the context of both the criminology literature and of their practical implications for crime deterrence and prevention. Additionally, in this final chapter I will discuss the various limitations to this study and make recommendations on improvements to this methodology for future research.

CHAPTER 8: CONCLUSIONS AND IMPLICATIONS

Overall, the goal of this study is to understand the ability, as well as what individual-level factors inform the ability, of respondents to identify crime locations in their neighborhood. To achieve this goal, this study first diagnosed the overall accuracy of hot spot identification in areas deemed to be problematic. Furthermore, this study took a first step at identifying the individual-level predictors related to individual demographics, perceptions of crime and disorder, and neighborhood familiarity and tenure that inform respondent accuracy. Addressing these questions is important because they have the potential to contribute to larger questions concerning the context of crime places. For instance, understanding which factors lead to better accuracy, and hence a better knowledge of who avoids or withdrawals from neighborhood locations, sheds some light on the types of people who go to these locations and those who do not, giving some insight into the context of these selected locations.

Review of Results

The first question this study addressed is whether respondents are accurate in including crime hot spots in the areas they identified as unsafe or dangerous. The findings here support those of past research in that respondents are not very accurate at identifying crime locations (Brantingham & Brantingham, 1981; 1997; Gillmartin, 2000). Overall, less than a quarter of respondents from both study communities, Belmont and Morvant, accurately included crime hot spots in their perceptions of dangerous or unsafe areas, even when testing for crime type and time of day variations.

Although I find that respondents are mostly inaccurate in their identification of crime hot spots, the results do show significant improvements in hot spot identification accuracies when crime and time of day conditions change. Past research recognizes a temporal difference in the way people report and conceptualize their fear of crime citing fear levels often increase with the onset of night (Skogan & Maxfield, 1981; Ferraro & LaGrange, 1987; Brantingham & Brantingham, 1997). This study confirms this finding. The paired t-test results reported here illustrate a significant shift in the accuracy scores when comparing day to night responses.

Additionally, the results of this study also suggest accuracy scores significantly improve when calculating respondent perception using violent crime hot spots versus general crime hot spots. The paired sample t-tests showed that respondents are more accurate at identifying violent crime hot spots than general crime hot spots, indicating that these types of crimes may be those that inform perceptions of danger and safety the most.

Interestingly, this study also found that, for the most part, respondents are quite accurate at predicting crime cool spot locations. Respondents are better at identifying these cool crime locations during the day and at night. This relationship is not as expected. The assumption was that poor knowledge of the crime hot spots would also lead to a poor knowledge of crime cool spots. This finding has led me to consider strongly the possibility that cool spot accuracy is a by-product of the size of the areas that respondents drew on their maps. For the most part, respondents identified very small areas as problematic (6.31% day; 9.39% night), thus improving their chances for accurately identifying most cool spots in the neighborhood. This possibility seems further supported by the descriptive analysis which suggests that respondents seem to be simply widening or enlarging the areas they consider unsafe or dangerous from day to night, explaining the decline in accuracy of cool crime spots for this time of day. Although I cannot confirm that these cool spots are the results of respondents "missing" hot spots, these results should be viewed with some skepticism.

The second goal of this study was to identify which individual-level predictors inform perceptions and accuracies of crime hot and crime cool spots in the neighborhood. Past cognitive mapping and fear of crime research indicate individual-level predictors can have a strong influence on these perceptions, leading to avoidance and withdrawal behaviors (Gillmartin, 2000). Thus, using zero-inflated count regression analysis and ordinal logistic regression techniques, I tested how factors related to individual demographics, perceptions of crime and disorder, and neighborhood familiarity and tenure affect hot and cool spot identification accuracies of respondents.

The results suggest that neighborhood familiarity is a significant predictor for the inclusion of crime hot spots in areas considered unsafe or dangerous. Although traditional studies do not include this concept, here we have seen that it has a consistent impact on whether respondents include a crime hot spot in the locations they consider unsafe or dangerous throughout their neighborhood. This prediction is significant for all hot spot models regardless of the time of day or type of crime examined. In fact, in the model that examined violent crime hot spots at night, I found a 42.1% increase in hot spot identification for every one-point increase in neighborhood familiarity score. The largest predictive effect found was for the general crime day model, which shows a 76.1% increase in hot spot accuracy scores for a one-point increase in neighborhood familiarity. Furthermore, the effect sizes are in the direction we would expect under the different model conditions – basically, the effects of neighborhood familiarity are most prominent for the day models, again illustrating the considerable influence of the night conditions on hot spot accuracy.

Gender also seems to be a solid predictor, however, not in the expected direction. These study results find that women are more likely than men to be accurate in their assessment of crime hot spots. Like the neighborhood familiarity findings, in the most conservative of circumstances (i.e., general crime hot spots during the day), the gender effect was most prominent. In that model men are half as likely as women to identify crime hot spots. The subsequent models suggest that there is between a 27.4% and 34.7% decrease in hot spot accuracy scores for men. Initially, I thought this finding might be the result of gender differences in the size of the location marked on the maps. However, independent samples t-test confirmed this is not the case. Instead, gender appears to be a significant predictor of accuracy. Overall, this finding supports recent research on risk-behavior decision-making (Park, et al., forthcoming).

Although this study finds social disorder to be significant in one of the hot spot models (violent hot spot day), it also approached significance at the lowered threshold of

.10 for the general crime hot spot day model and the violent crime hot spot night model. In all models, the relationship between perceptions of social disorder and accuracy is that respondents who have higher perceptions of social disorder are more accurate in their identification of crime hot spots in the community. These results fall in line with past research in that it suggests people who are more aware of instances of social disorder in their neighborhood are better at accurately identifying crime locations as unsafe or dangerous (Gillmartin, 2000; Nasar & Fisher, 1993).

What is most interesting is that the effect of perceptions of social disorder seems more prevalent with violent crime hot spots. A recent study by Yang (2008) suggests that there are significant correlations between violent crime hot spots and locations that have high levels of social disorder. In thinking about how this larger findings impacts avoidance and withdrawal areas, we again see a situation where the perceptions of social disorder can lead to avoidance or withdrawal from these locations. Although this finding is not as strong as others in the study, it does suggest that future research needs to further test this relationship.

The results for cool crime spots models were much different than that for the crime hot spot models. Specifically, only one predictor was consistently significant, which was the control variable, percent of the map marked. However, the perception of physical disorder predictor did reach or approach significance at the lowered threshold of .10 for both the day and night cool spot models. Overall, the results suggest that people who have lower perceptions of physical disorder are more likely to accurately identify crime cool spots. This finding is actually in line with what the original predicted hypotheses. When we think about this practically, this result does not seem out of line considering that people who have better opinions of the neighborhood might be less likely to mark larger areas on the map. However, any practical implications from this finding need to be considered with caution in that the way cool spots were constructed in this study might not be the best way to measure this concept. I will discuss this issue a little further in the limitations section below.

Although not as strong, this study also found significant effects for the predictors of age, education, marital status, and crime as a top three problem in the neighborhood, and length of residency in at least one the four hot spot models. For four of these predictors the tested relationships were in the hypothesized direction. Specifically, respondents who were older, better educated, married or had been married, and named crime as a top three neighborhood problem were better at accurately identifying crime hot spots in their perceptions of dangerous or unsafe locations in the neighborhood. Additionally, length of residency was found to be significant in the hot spot day model; however, this relationship was not in the expected direction. Instead, the results suggest that respondents who had lived in the community a shorter amount of time were more likely to accurately include crime hot spots in the areas they consider unsafe or dangerous.

These results, although potentially promising, also need be viewed with some caution. The effects for these predictors were marginal and just reached or approached the significance threshold. The best implication that can be made concerning these predictors at this point is that scholars interested in this form of research should consider including them in future studies. Additionally, these results show some marginal support for the inclusion and consideration of fear of crime measures when explaining knowledge and patterns of people in their neighborhoods and the potential implications for the context of these places.

Finally, I think it is important to mention that there were a number or predictors that never showed a significant predictive relationship in any of the models. Ethnicity, crime as reason to avoid marked areas, and time spent outside of the community per week all have non-significant relationships with crime hot spot and cool spot accuracy scores, regardless of type of crime or time of day tested. Although the findings indicate these are not significant predictors, this does not mean that future research should exclude these measures. It is important to keep in mind that this study is an initial attempt to use these measures to explain avoidance and withdrawal actions of individuals. It is entirely possible that if I had constructed the dependent measures differently or if I had used different questions to measure these concepts, I would have found significant results. I will discuss these possible study limitations later in this chapter. However, I think it is critical to state that it is just too early in this research path to exclude these measures from consideration.

Discussion of Results

Earlier, I argued that this study could contribute to the larger field of criminology in that it could help explain the context of crime places. I proposed that people are aware of crime places and purposefully avoid and withdrawal from these locations, resulting in crime concentrations and sustainment in these locations. Yet, the results here do not necessarily support this argument. For the most part respondents are inaccurate at identifying high crime locations, suggesting that they have no reservations about traveling to these areas.

Still, these results can be used to help explain the context of these high crime places using rational choice theory and routine activity theory. Consider routine activity theory, which states that motivated offenders, suitable targets, and the lack of capable guardians must converge in time and space. Under the direction of this theory, if a person does not know where crime is, they are likely to still travel to and through these locations and serve as potential targets for victimization, making the supply of suitable targets plentiful in the crime hot spot locations.

Furthermore, the findings here are useful when thinking about the element of guardianship. It might be the case that not all guardians are created equal. It is possible that the demographics which have significantly better accuracy scores (women, people high in neighborhood familiarity, people with high perceptions of social disorder) are more effective guardians at these locations. For instance, it might be that women are more likely to speak out about crimes or that people who are more familiar with the neighborhood are also more familiar with the people within the neighborhood, making their guardianship more effective in that they can identify offenders.

Rational choice theory is also useful when considering the results of this research. Recall that in the field of criminology, discussions of rational choice theory are traditionally in the context of offender decision-making (see Clarke & Cornish, 1985;

Cornish & Clarke, 1986). Under rational choice theory, an offender makes a rational cost-benefit assessment, about a crime opportunity. If in fact the benefit outweighs the cost, the theory suggests that the offender will take advantage of the opportunity and crime will ensue. The theory further argues that these decisions are informed by both situational selection, or instances where offenders have an easy target, a low likelihood of being caught, and a high expected reward and bounded knowledge (Cornish & Clarke, 1986).

I propose that this decision framework can be extended beyond offender decision-making and can be applied to everyday assessments of victim risk at places. In these instances the costs and benefits weighed shift to where the cost is the likelihood of victimization and the benefit is the ability to travel to and through a place. Like traditional notions of rational choice theory, this new decision framework is also informed by both situational selection and bounded knowledge. Essentially, these assessments of travel risk have to be made with the information that is unique to each person.

When we think about the initial findings regarding respondent accuracy, it is easy to see how these findings are explainable through the notion of situational selection. Essentially, the time of day or the type of crime can inform respondents in different ways. In my application of situational selection to victim risk at places, I suggest that the elements that inform decisions are risk of vulnerably, likelihood of guardianship, and reward of safety or non-victimization. The assessment of each of these situational factors are bound to change when processing different forms of information (e.g. day versus night; domestic violence versus rape). Therefore, the findings illustrate exactly what is expected – the situational factors change therefore altering the situational selection of places to people.

The predictive results of this study are also supported through this risk assessment framework. For instance, this study concludes that those who are more familiar with their neighborhood are more accurate at including crime hot spots in the areas they consider to be unsafe. This finding followed the expected prediction. Logically, those with more familiarity of the neighborhood have more information about the dynamics of places in the neighborhood. Thus, the decision-making constraints are different for these respondents than for those who are less familiar with the neighborhood. This all suggests that improved information about the neighborhood can lead to less decision boundaries of places and therefore a better ability to assess a place.

The application of this framework to the finding for gender is a little more tricky, but still worthwhile. Essentially, this study found that women are more accurate at identifying crime hot spots in their assessments of unsafe areas in the neighborhood. This study did not collect information that would allow me to decipher if this is due to better information or knowledge that women might have at places (e.g., this can be obtained vicariously, through news sources, research, etc.) or if it is an effect that stems from women having a higher sensitivity to risk, or both. What it does mean is that women essentially have more relevant information that informs their cognitions of place, making their assessments more accurate.

The take away point from this discussion is that the principles of rational choice theory, which is often used to explain offender behavior in routine activity theory, are applicable to the decisions that community residents make about places within the neighborhood. Under both opportunity theories, the assumption is that offenders are rational actors who are trying to maximize crime opportunities (e.g., situations that contain suitable targets and decreased guardianship). However, we can also think of residents, who are potential victims and guardians, in the same way. These people also use rational decision-making when determining safe and unsafe locations (e.g., places that have higher guardianship) within the neighborhood. This framework helps illustrate the utility of the study findings.

Study Limitations

As with any body of research, there are limitations to this study that merit consideration. First, there are issues with the sample in both its size (N=152) and in the sampling strategy. The sample size was limited because of resource and time constraints. This survey was only a small part of a much larger project that aimed to reduce violent crime in troubled communities of Trinidad and Tobago. Additionally, when researchers administered the survey they considered the possibility that perceptions of problem locations could change based on the prevalence and impact of current events. Since the areas surveyed were among the most active for violent crime, they wanted to ensure that participants had the opportunity to respond in a very short time frame to reduce the effects of history bias on the sample. It is possible that the small sample size used in this study is affecting the outputs of the regression results. For instance, the individual level predictors that reached or approached significance at lowered thresholds might be significant if the sample consisted of more responses.

Second, the study did not randomly sample for survey participants. Instead, the sampling strategy here consists of a snowball sampling methodology of active participants in key community groups including churches and neighborhood improvement projects. Again, this strategy was used in response to both limited time and resources for the survey administration. It is possible that the survey sample contains some bias in that it over/under represents certain population demographics such as age, gender, ethnicity, etc. For instance, when we compare the number of female respondents in the study (30.4%) to the overall population of the neighborhoods (52.7% Belmont; 51.3% Morvant) and of Trinidad and Tobago (50.1%), we see that women are under-represented in this study. Overall, this limitation should not take away from the findings which are still quite meaningful because the participants represented here are likely those who are active and engaged in their neighborhoods.

In addition, there are potential issues with the construction and measurement of the dependent variables. The goal of this study was to assess the accuracy with which respondents were able to identify hot and cool crime spots in their neighborhood. However, the questions used to construct the dependent variable asked respondents about safety and perceptions of danger or risk, not about specific crime locations, such as crime hot spots and crime cool spots. A brief analysis of the open-ended question asking why respondents marked the areas they did revealed they did so because of concerns about crime but also because of fears and concerns about the problems associated with the areas and the people within them. Therefore, it is quite possible that the effects uncovered in this study are the results of both direct and indirect relationships between the individual-level predictors and accuracy. For instance, the effects found here may be direct effects. However, it is also possible that unmeasured constructs, such as fear or concerns about victimization, are mediating these relationships. Unfortunately, our survey instrument did not contain questions to measure these phenomena.

A fourth potential limitation to this study is the quality of the crime data. Specifically, the E-999 calls for service data contained geographic information for less than half of the reported calls for service for the nation of Trinidad and Tobago. I attempted to test for these biases (see Appendix D) and found that there does not seem to be any bias in the calls that have location information across call types. Yet, when I examined the calls for service for homicide with location information against the homicide incidents that had location information, less than half of the E-999 homicide calls matched the incident data. Although this was the case, not much can be drawn from that analysis because comparing the calls for service data to the crime incident data could be inappropriate. For instance, there could be classification problems in the calls that actually relate to the homicide incidents (i.e., could be coded as shooting, disturbance, etc.)

Regardless, the E-999 crime data is potentially problematic in that the calls for service data may have a location bias. Specifically, the geographic information included in the report data might be limited to certain geographic areas (e.g., areas that are accessible by vehicle). This means that E-999 dataset may not record accurate location information for areas that are not easily accessible to police vehicles. Likewise, this data may have resulted in inaccuracies in the cool spots throughout a neighborhood in that these locations may contain some crime. If either of these scenarios are true, it would create a misrepresentation in the accuracy with which respondents include crime areas in their perceptions of problem locations.

Moreover, the crime data source used here may be biased in that it under-represents actual criminal activity. In other initiatives conducted by the Crime Reduction Initiative team, qualitative interviews revealed that many people who live in the two areas that are under study do not necessarily believe that police officers will respond when called and often believe that the police cannot do anything about crime overall. Additionally, the areas represented here are among some of the poorest in the nation, with many squatters taking up illegal residency. It is likely that respondents living here may have limited access to telephones, making it difficult to access the police. These sentiments could lead to underreporting of crime to police, affecting these data, again making it possible for crime hot spot accuracy scores to be undercounted or for cool spot accuracy to be overrepresented.

Fifth, it could be the case that grouping these two Trinidadian communities together masks effects that might hold true for only one of the neighborhoods. Because the grouped community sample sizes are so small, it was impossible to test the effects of the predictors on the two community samples individually. However, it is possible that the study predictors work differently for respondents from the two different communities.

For example, it may be the case that the marginal effects reported here are non-existent for one community and hold strong for the other.

A final limitation to this study is that the hypothesized relationships are derived from theory and research in the United States, yet they are applied to an international location. Even though the Community Problems and Issues Survey was pre-tested in Trinidad, the possibility exists that the content on the survey may not hold the same meaning in Trinidad and Tobago as it does in the United States (e.g., indicators of disorder). Moreover, although we used native interviewers as a way to deal with potential issues of poor education and illiteracy, respondents may have had a limited ability to read and understand maps.

Similarly, crime may not operate the same way in Trinidad and Tobago as it does in the United States. The theories and ideas used in this study are largely based on opportunity theories (i.e., rational choice theory; routine activity theory). While opportunity theories have been studied extensively in developed, Westernized nations there have been no documented studies to date from Trinidad and Tobago. It is relevant to consider that these theories are not applicable in Trinidad and Tobago. For instance, crime may occur even with the presence of guardianship in these two Trinidadian communities. It could be the case that citizen who live in these areas are less likely to report crime activities to police because of fear, alliances to offender, or even low trust in the police. Thus, without knowing if opportunity theories apply to Trinidad and Tobago, this issue will remain a potential problem for consideration.

Implications for Prevention Efforts

Since this study is exploratory and enters new research ground, the implications for practice and policy are limited. Regardless, there are still a number of key suggestions for both policy and research. Specifically, these results suggest that steps need to be taken to improve knowledge of crime locations among residents, hopefully resulting in reduced crime across these problematic locations. Likewise, this study shows some promise and illustrates that more studies such as this might be useful in diagnosing the context of crime at places. I briefly discuss each of these implications below.

A first step toward prevention could be case assessments of the locations most commonly marked as dangerous or unsafe by respondents, which may or may not be reflective of actual crime in the neighborhood (recall the possible issues with the crime data). These assessments could include systematic social observations of the environments and the people within them at different points throughout the day. From what we know in disorder studies, improvements to both social and physical disorder often have the ability to improve both individual and collective guardianship within locations. Consequently, these assessments could determine different strategies aimed to improve the social and physical environment to help residents feel more secure about these locations.

A second prevention strategy would be to educate community residents on the locations and prevalence of crime in their communities. At the time of this study, there were a few community-level grass-roots efforts, organized primarily through church and community groups, to reduce the violence in these communities, particularly among gangs. However, in these meetings that focused on the community efforts, little attention was paid to the locations of actual crime; instead attentions were often directed at the people that were considered to cause problems. A better approach might have been for these motivated groups to have the information about crime places to educate the people in the community. Because of the low levels of police legitimacy among Trinidad andTobago residents, this education might be better received from these community-based groups versus the police department.

Unfortunately, until we know more about what informs perceptions and how those perceptions tie into the context of places, the implications for action are limited. Therefore, I also address a number of implications for future research below.

Implications for Future Research

When considering the limited prevention implications of this study, it is useful to consider the implications this study has for future research. First, these results indicate that cognitive maps can be a useful methodology in understanding people's perceptions of problem locations. Overall, there were certain locations that over 50% of the sample identified as problematic (see Appendix H). Although there are areas that have strong levels of consensus, it is not always the case that these areas correlate with high crime locations. This could be the result of two things. First, it could be that other processes are informing these perceptions including an association to people or groups who inhabit these areas. Second, it could be that the crime data used in this study is not a true representation of actual crime hot spots. To explain this consensus among mapping responses, future research should use two types of mapping exercises, those that ask about areas they avoid and those that ask about both general and violent crime hot spots. Future studies should also follow-up the mapping exercise with more detailed questions about why each area was marked. Additionally, researchers should use multiple crime data sources to get at the best geographic representation of crime in study areas to ensure that the correct data is used in the construction of the dependent measures.

Furthermore, future research needs to test both direct and indirect relationships between individual level predictors and the accuracy with which respondents identified crime hot spots in their cognitions of unsafe/dangerous areas. The results of this study indicate that certain measures, such as gender and neighborhood familiarity, are consistent predictors of accuracy scores. Likewise, a number of other predictors including social disorder, age, education, and length of residency were found to have some effects. I mentioned previously that the relationship between these predictors and accuracy could be mediated by a concept such as fear level. It is quite likely that fear could inform perceptions of disorder (e.g., more fearful residents are more likely to see social disorder as a problem), which in turn could affect a person's ability to identify actual crime hot spots. There are a number of different possible secondary relationships, and future studies might benefit from collecting information on these types of measures.

Finally, it is imperative that future research include more stringent methodology procedures. In the section above, I discuss issues with the sample method and the sample size. Specifically, this study used a snowball sampling strategy where the number of collected surveys came under the desired minimum threshold. Future studies would benefit from an improved response rate and the use a sampling methodology, such as cluster random sampling, to ensure the closest representation of community respondents. One way to do this might be to focus on just one community. Overall, increasing the sample size and making the sample more reflective of the whole community, not just those who are most likely to be active or engaged, will lead to an improved confidence in the study findings.

Conclusions

To conclude, this study addressed two questions concerning hot spot identification. First, it examined how accurate respondents are at identifying hot and cool crime spots within their neighborhoods. Furthermore, this study examined the influence of select individual predictors on respondent accuracy. Overall, it was found that respondents are relatively inaccurate at identifying crime hot spots in their community. However, it was found that accuracy scores improve when the time of day conditions change from day to night and when the crimes used to construct the hot spots are violent personal crimes versus general crimes.

The crime cool spot accuracy analysis revealed that respondents are quite accurate at not including any of the ten randomly selected cool spots in their perceptions of problematic places. However, this finding must be viewed with caution since the number of crime cool spots in the community is so high, the chances of not including many of the ten are relatively great. Furthermore, respondents were not asked to specifically decipher crime and non-crime locations so it is problematic to infer that the cool spot indices are a good representation of cool spot knowledge.

When examining the influence of individual predictors on the variation of hot spots and cool spots it was found that women and people who are more familiar with their neighborhood have more accurate hot spot identification scores in their perceptions of areas that are unsafe or dangerous in the community. Furthermore, in some models, the perceptions of social disorder had a significant impact – essentially, those reporting higher instances of social disorder had more accurate perceptions of crime hot spots. The cool spot analysis revealed that one predictor, perception of physical disorder, might have some influence; however, this finding was not consistent and needs to be viewed with caution because of the measurement issues previously cited.

In thinking about the larger implications of these findings, it is useful to view these results in the framework of opportunity theories. However, unlike traditional opportunity theories, these findings help explain the decision-making of potential victims rather than offenders and the focus changes from a crime opportunity to an opportunity to prevent victimization. This connection is natural considering prior connections between rational choice theory and routine activity theory. As with offender focused routine activity theory, these decisions are bounded by a number of conditions, including those found to be significant in this analysis – gender and neighborhood familiarity. Overall, these bounded rational decisions inform a respondent's choice to go or not go to a place, impacting the routine activities of these locations, including the availability of victims as well as the influence of guardianship. Subsequently, more research is needed to understand the context of these dynamics.

In addition to the findings, this study presents a number of relevant practice and research implications. Since we still know very little about the dynamics of people within both crime and non-crime places, my practice implications are limited to suggestions about diagnosing and educating residents on areas that both respondents feel are problematic and those that are actually problematic in the community.

APPENDIX A

Community Problems and Mapping Survey
Informed Consent Form

Research Procedures
This research is being conducted to understand how residents view your community, and to identify ways to improve the services provided to communities like yours. If you agree to participate, you will be asked a series of questions that will take about 30 minutes to answer. You will also be asked to mark locations on a map of your community. You must be at least 18 years old to take part in the study.

Risks
There are no foreseeable risks for participating in this research.

Benefits
There are no direct benefits to you as a participant, other than furthering research in this area.

Confidentiality
The information gathered during this interview will be anonymous. Neither your name nor any other identifying information will be written on the questionnaire. This interview will be audio-recorded to ensure I accurately report your answers. Your identity will not be recorded or reported on the audiotape or the interview transcript. Once the audio tapes have been transcribed, the tapes will be destroyed.

Participation
Your participation is voluntary, and you may stop the interview at any time and for any reason. If you decide not to participate or want to stop the interview, there is no penalty. There are no costs to you for participating in this interview. If you complete the interview, you will receive $100 TT.

Contact
This research is being conducted by Devon Johnson in the Administration of Justice program at George Mason University. She may be reached at 703-993-8424 (or by mail at 10900 University Blvd, MS 4F4, Manassas, VA 20110) for questions or to report a research-related problem. You may contact the George Mason University Office of Research Subject Protections at 703-993-4121 (or by mail at 4400 University Drive, MS 4C6, Fairfax, VA 22030) if you have questions or comments regarding your rights as a participant in the research. This research has been reviewed according to George Mason University procedures governing your participation in this research.

The George Mason University Human Subjects Review Board has waived the requirement for a signature on this consent form. However, if you wish to sign a consent, please contact Devon Johnson using the information listed above.

Consent
I have read this form and agree to participate in this study.

_____ I agree to audio taping

_____ I do not agree to audio taping.

Community Problems and Mapping Survey

INTRO SCRIPT

Hello, my name is ___________________________ [FIRST NAME ONLY]. I am conducting interviews as part of a research project in several communities. The purpose of this research is to learn what residents think about living in these communities and to identify some of the problems and issues residents face. By participating in this interview and sharing your views, you will be providing important information which will be used to make recommendations for improvements in communities like yours.

I would like to ask you a series of questions that will take about 30 minutes to answer. You will also be asked to mark locations on a map of your community. You must be at least 18 years old to take part in the study. If you participate, you will be paid $100 TT in cash at the end of the interview.

There are no foreseeable risks for participating in this research, and there are no benefits to you individually. The information you provide during this interview will be confidential. I will not write down your name or any other identifying information on the questionnaire. With your permission, this interview will be audiotaped to make sure I have recorded your answers accurately. You will not be identified on the audiotape. Your participation is voluntary. You can refuse to answer any question, and you may stop the interview at any time and for any reason.

Do you have any questions? Would you like to participate in this research project?

[IF YES, GIVE ACKNOWLEDGEMENT FORM] This form explains the purpose of the research and summarizes the information I have just told you.

Community Problems and Mapping Survey

[COMPLETE QUESTIONS 1-4 BEFORE INTERVIEW. TURN ON THE AUDIOTAPE, AND SPEAK THE INTERVIEW INITIALS, DATE, TIME AND INTERVIEW NUMBER INTO THE RECORDER.]

________ Interviewer Initials

________ Date of Interview

________ Time of Interview

________ Interview Number

This survey will require your undivided attention. We ask that you kindly mute or power off your cellular telephone for the duration of the interview.

I want to begin by asking you some general questions about the community in which you live. Please answer these questions to the best of your knowledge.

In what community do you reside?

BELMONT COMMUNITIES	MORVANT COMMUNITIES	
____ Belmont	____ Malick	____Never Dirty
____ Gonzales	____ Mon Repos	____Romain Lands
____ Upper Belmont	____ Morvant	

How long have you lived in your community? ______ Months ______ Years

How long have you lived at your present address? ______ Months ______ Years

Now I'm going to ask you about locations within or near your community. I would like you to tell me if you are completely familiar, familiar, unfamiliar or completely unfamiliar with each location.

Completely familiar means you have detailed recollection and knowledge of the location. Completely unfamiliar means you have no knowledge or recollection of the location.

[IF FROM MORVANT, SKIP TO QUESTION #17]

How familiar are you with the locations of…[SHOWCARD=1]

BELMONT COMMUNITIES

	Completely Familiar	Familiar	Unfamiliar	Completely Unfamiliar	DK	NA	Ref
8. Port of Spain General Hospital	4	3	2	1	77	88	99
9. Belmont Police Station (Current)	4	3	2	1	77	88	99
10. Hindu Temple	4	3	2	1	77	88	99
11. Gonzales Community Center	4	3	2	1	77	88	99
12. Glouster Lodge Morvian School	4	3	2	1	77	88	99
13. Mt. Carmen Baptist Church	4	3	2	1	77	88	99
14. St. Martin de Porres Catholic Church	4	3	2	1	77	88	99
15. St. Rosary Catholic Church	4	3	2	1	77	88	99
16. Escalier School	4	3	2	1	77	88	99

[IF FROM BELMONT, SKIP TO QUESTION #27]

MORVANT COMMUNITIES

	Completely Familiar	Familiar	Unfamiliar	Completely Unfamiliar	DK	NA	Ref
17. St. Dominick Catholic Church	4	3	2	1	77	88	99

	Completely Familiar	Familiar	Unfamiliar	Completely Unfamiliar	DK	NA	Ref
18. Morvant Police Station (Current)	4	3	2	1	77	88	99
19. Fernandes Compound	4	3	2	1	77	88	99
20. Neal & Massey Nissan Dealership	4	3	2	1	77	88	99
21. The Church on the Rock	4	3	2	1	77	88	99
22. Daybreak Assembly	4	3	2	1	77	88	99
23. Morvant Northern Government School	4	3	2	1	77	88	99
24. Malick Senior Comprehensive	4	3	2	1	77	88	99
25. Morvant Anglican School	4	3	2	1	77	88	99
26. Maritime Mall	4	3	2	1	77	88	99

27. What are the three biggest problems in your community?
(a)____

(b)____

(c)____

Now I'm going to read a list of things that are problems in some neighborhoods. For each, please tell me if it is a big problem, somewhat of a problem, or not a problem in your neighborhood. [SHOWCARD=2]

How much of a problem is/are……?	A big problem	Somewhat of a problem	Not a problem	DK	REF
28. Trash and garbage on the sidewalks/street	3	2	1	77	99
29. Graffiti on buildings and walls	3	2	1	77	99

How much of a problem is/are……?	A big problem	Somewhat of a problem	Not a problem	DK	REF
30. Vacant or abandoned houses/buildings	3	2	1	77	99
31. Poor lighting	3	2	1	77	99
32. Abandoned cars	3	2	1	77	99
33. Empty or overgrown lots of land	3	2	1	77	99
34. Groups of teenagers or adults hanging out in the neighborhood and causing trouble	3	2	1	77	99
35. People buying and selling drugs on the street	3	2	1	77	99
36. People drunk in public/on the street	3	2	1	77	99
37. People smoking marijuana in public	3	2	1	77	99
38. Loud or unruly neighbors	3	2	1	77	99
39. Vagrants/homeless people	3	2	1	77	99
40. Truancy/youth skipping school	3	2	1	77	99

For the next few questions, please tell me if you would be very fearful, somewhat fearful, or not fearful in the following situations. [SHOWCARD=3]

	VF	SF	NF	DK	REF
41. If you were involved in a car accident	3	2	1	77	99
42. If a stranger stopped you in your neighborhood to ask for directions	3	2	1	77	99
43. If you were walking alone in your community, during the day	3	2	1	77	99
44. If you were walking alone in your community, at night	3	2	1	77	99
45. If you were walking with other people, in your community, during the day	3	2	1	77	99
46. If you were walking with other people, in your community, at night	3	2	1	77	99
47. If you were answering a knock at your door after dark	3	2	1	77	99
48. If your car was stolen	3	2	1	77	99
49. If your house was broken into	3	2	1	77	99

Now we are going to change topics again.

50. Do gangs exist in your community?	**Yes**	**No**	**c**	**REF**
	1	0	77	99
		(IF NO, DK, OR REF, SKIP TO Q55)		

51. How many gangs would you estimate exist within your community?_________
[PROBE: If you had to guess…] (DK=77) (REF=99)

Please tell me if you strongly agree, mostly agree, mostly disagree or strongly disagree with the following statements. [SHOWCARD=4]

	SA	**MA**	**MD**	**SD**	**DK**	**NA**	**REF**
52. Gangs are a problem in my community	4	3	2	1	77	88	99
53. Gangs are helpful to my community	4	3	2	1	77	88	99
54. Gangs are necessary to my community	4	3	2	1	77	88	99

The next few questions ask about different areas in your community. I will give you a set of maps and ask you to draw on them with these markers.

As you can see, this is a map of your community. All of the streets are labeled with their names. Also, the landmarks and locations that were mentioned earlier in the survey are highlighted and labeled. Please take a few moments to familiarize yourself with the map.

[GIVE RESPONDENT MAP #1 AND PURPLE MARKER]

55. Using the purple marker, please place a dot on this map where you currently live.

[PROBE: IF RESPONDENT ASKS WHY, INFORM THEM IT IS AN EXERCIZE TO HELP ORIENT THEM WITH THE MAP AND IT WILL NOT, IN ANY WAY, BE USED TO IDENTIFY WHO THEY ARE]

[STILL USING MAP #1, GIVE THE RESPONDENT THE RED MARKER]

56. Next, with the red marker, please outline the areas on this map that you would NOT feel safe going to during the DAY.

[STILL USING MAP #1, GIVE THE RESPONDENT THE GREY MARKER]

57. Now, using the grey marker, please outline the areas on the map that you would NOT feel safe going to during the NIGHT?

[STILL USING MAP #1, GIVE THE RESPONDENT THE GREEN MARKER]

58. Using the green marker, please outline areas on the map that you would advise someone from OUTSIDE of your community NOT to go?

59. Why would you advise them to stay away from these areas?
____
____
____

[IF RESPONDENT ANSWERED "NO" TO QUESTION #50, SKIP TO QUESTION #61.]

[COLLECT MAP #1 FROM RESPONDENT AND GIVE THEM MAP #2 WITH ALL OF THE MARKERS.]

60. Earlier you mentioned that gangs exist in your community. Using a different color for each gang, please draw the primary areas of your community that each gang controls.

For example, use the blue marker to outline the area that Gang #1 controls. Use the red marker to outline the area that Gang #2 controls, etc.

We are now in the final section of the interview. The last few questions ask about basic demographic information. Again, these questions cannot be used to identify you as a respondent.

61. What is your age? _______ # years old

62. Gender (BY SIGHT):
Male=1
Female=2

63. What is your racial/ethnic background?
1=African/Afro-Trinidadian
2=East Indian/Indo-Trinidadian
3=Mixed
4=Other (Specify)______________________
77=DK
99=REF

64. What is the highest level of formal education that you have attained?
1=None
2=Primary
3=Junior secondary
4=Secondary
5=Technical/Vocational
6=Tertiary/University
77=DK
99=REF

65. What is your current marital status?
1=Single, never married
2=Living with someone, but not married
3=Married
4=Separated/Divorced
5=Widowed
77=DK
99=REF

66. How many children do you have? ________

67. How many people reside in your house? ________

68. In what community did you reside during childhood? ________

69. On average, how many days per week do you leave your community for work, shopping, socializing, etc.? ___________

INTERVIEWER OBSERVATIONS
Complete at the end of each survey. The following observations will be used to gain an understanding of respondents' reactions and cooperation levels. Please circle the number that best represents the interview.

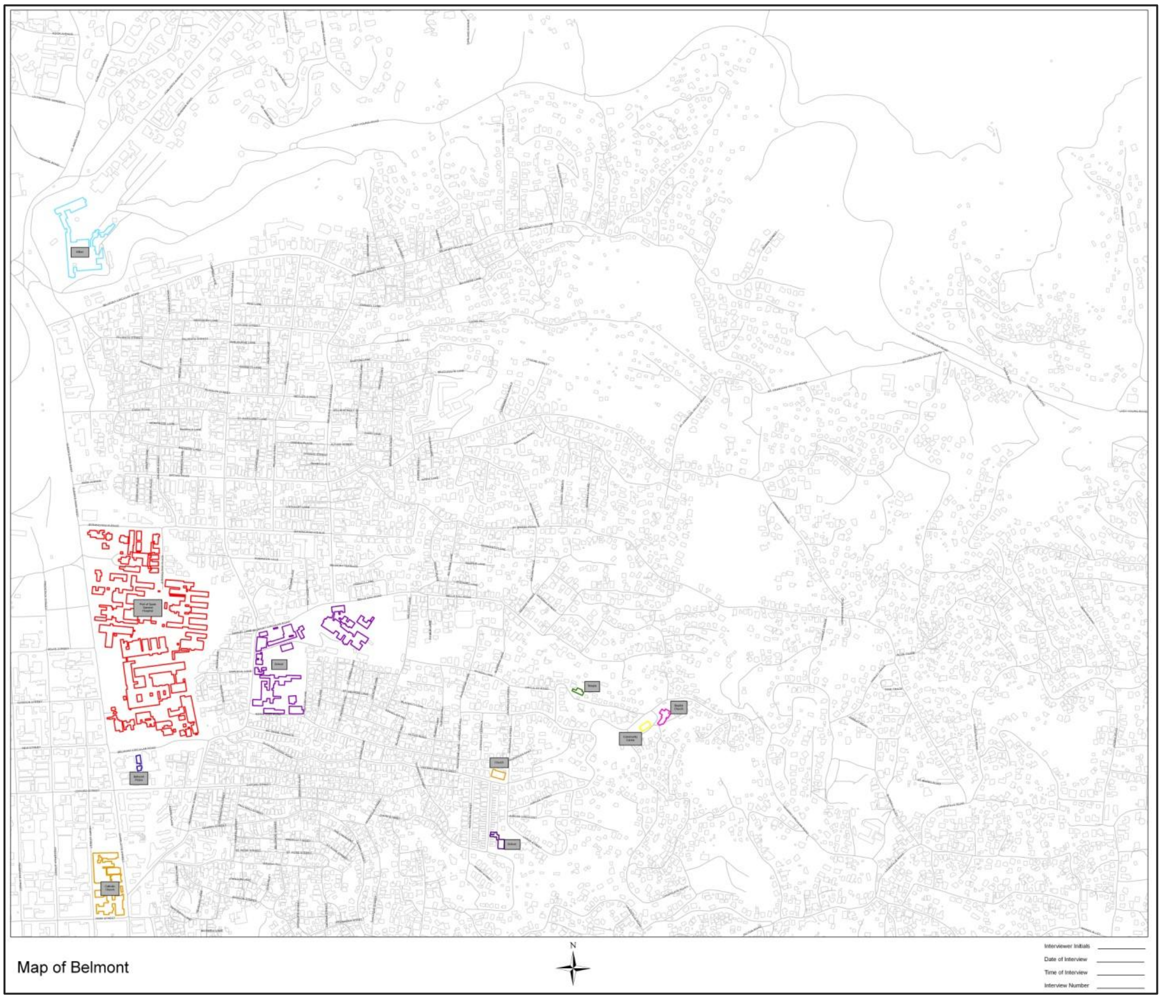
THE RESPONDENT….

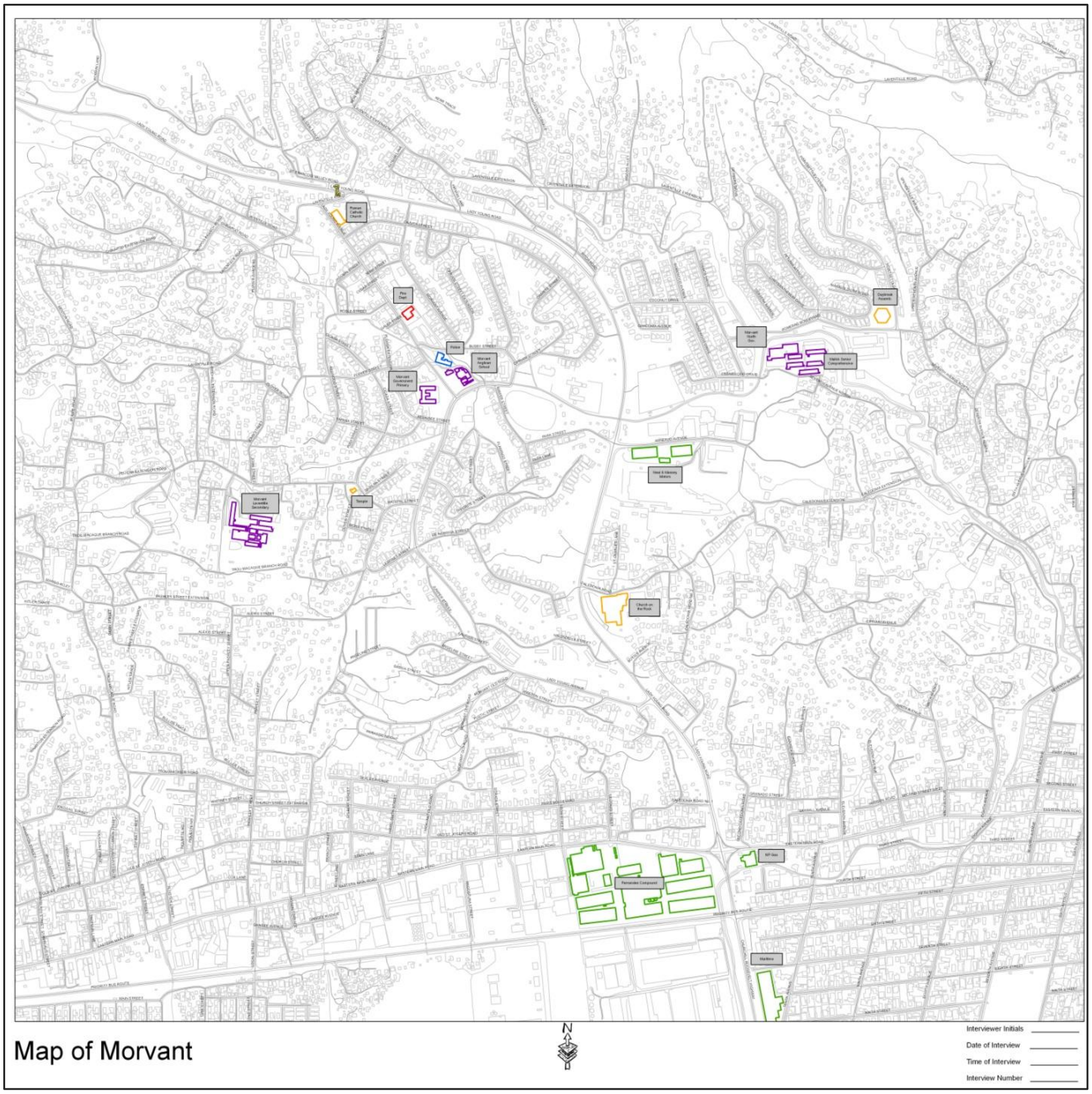
70. Remained attentive throughout the survey	Attentive	5	4	3	2	1	Inattentive
71. Remained cooperative throughout the survey	Cooperative	5	4	3	2	1	Uncooperative
72. Needed clarification with questions	Needed a lot of clarification	5	4	3	2	1	Did not need any clarification
73. Needed clarification with the maps	Needed a lot of clarification	5	4	3	2	1	Did not need any clarification
74. Needed assistance reading the maps	Needed a lot of assistance	5	4	3	2	1	Did not need any assistance
75. Seemed forthcoming with information throughout the survey	Completely forthcoming	5	4	3	2	1	Not at all forthcoming
76. Seemed nervous throughout the survey	Nervous the entire survey	5	4	3	2	1	Not at all nervous
77. Seemed reluctant to answer questions on the survey	Reluctant the entire survey	5	4	3	2	1	Not at all reluctant
78. Seemed to use roads and landmarks to identify dangerous places and gang areas	Always used roads and landmarks	5	4	3	2	1	Never used roads and landmarks
79. Seemed aware of audio recording device throughout the survey	Always seemed aware	5	4	3	2	1	Never seemed aware of audio recording device

80. Please list the questions that respondents seemed reluctant to answer:

81. Additional comments about the interview:

APPENDIX B


Map of Belmont
N
Interviewer Initials
Date of Interview
Time of Interview
Interview Number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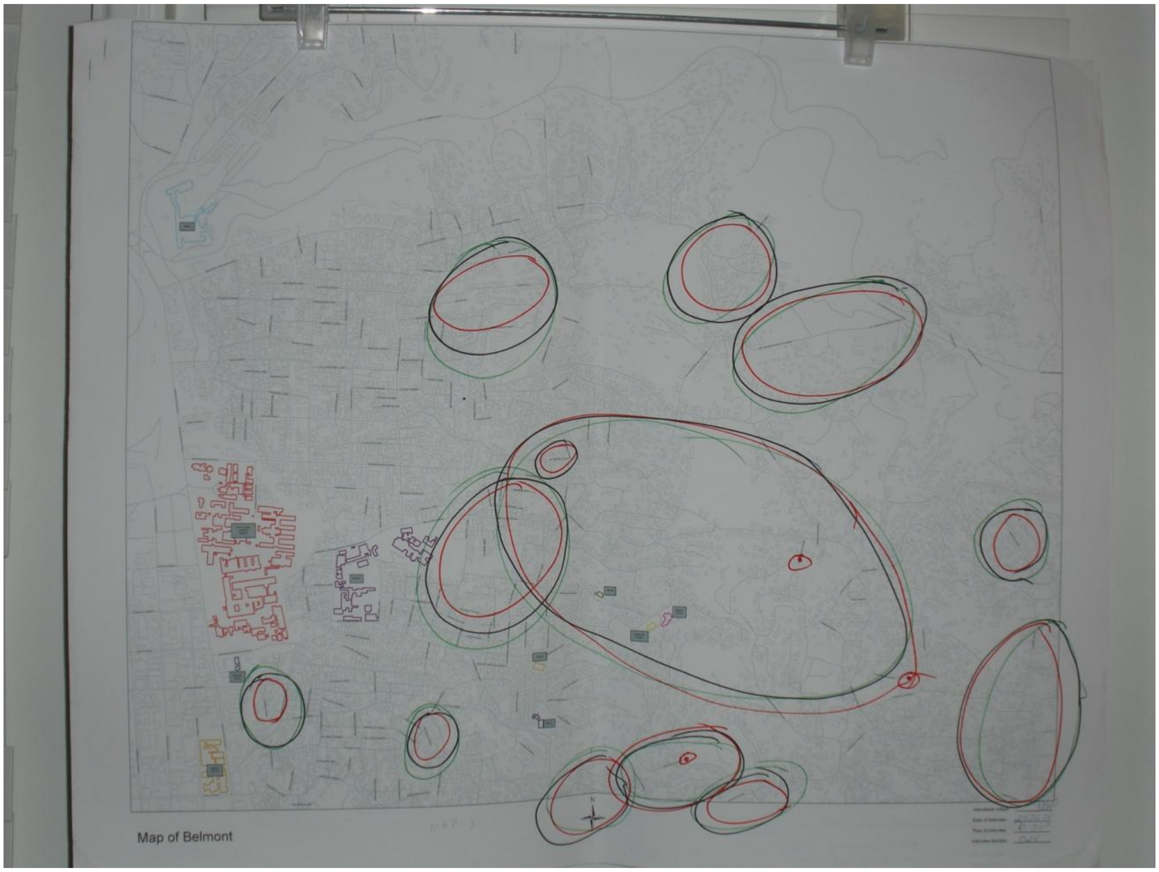
Date of Interview
Time of Interview
Interview Number

APPENDIX C


Map of Belmont

APPENDIX D

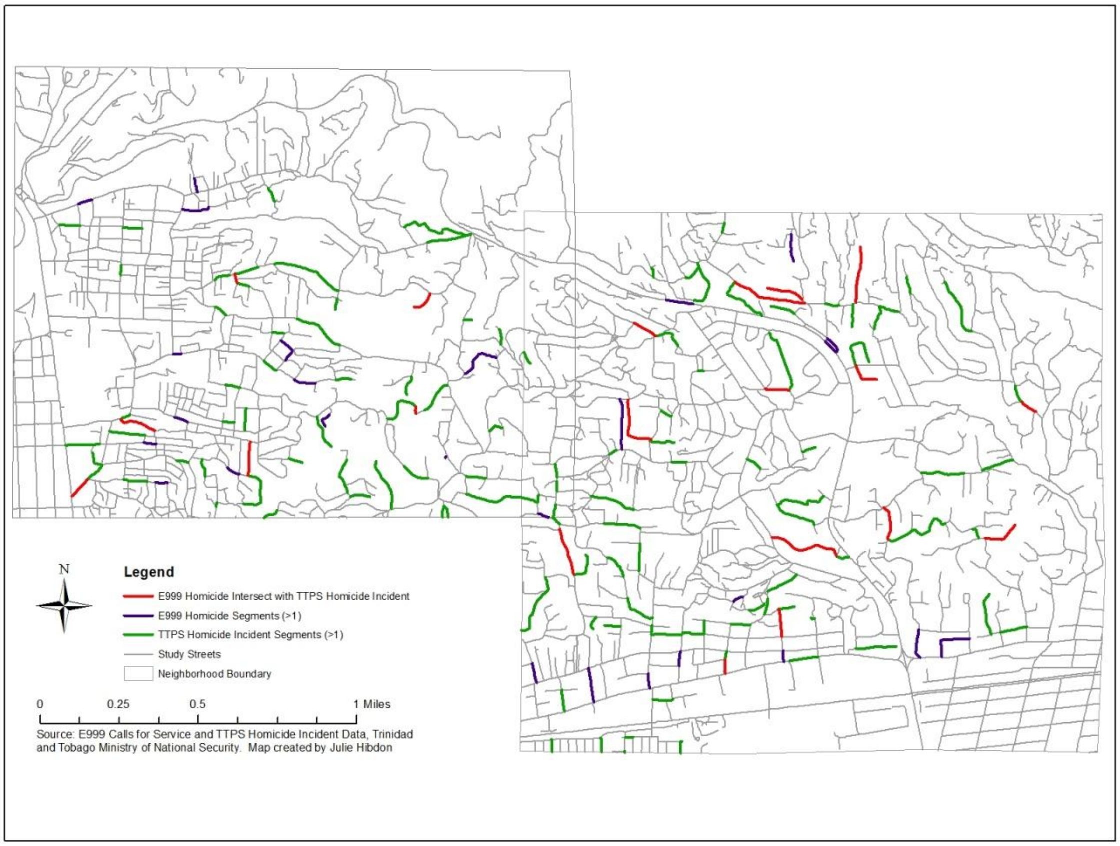
Comparison of Matched and Unmatched E999 Calls for Service by Crime Type

Call Description	Unmatched Count	Percent Unmatched	Matched Counts	Percent Matched	Total Counts	Percent Total
None	18,671	93.20	1,362	6.80	20,033	100.00
Threat	11,380	50.15	11,312	49.85	22,692	100.00
House break-in	3,028	46.55	3,477	53.45	6,505	100.00
Robbery	5,320	49.91	5,339	50.09	10,659	100.00
Rape	251	48.74	264	51.26	515	100.00
Domestic violence	25,510	49.58	25,946	50.42	51,456	100.00
Community Service	400	38.72	633	61.28	1,033	100.00
Assault	5,135	46.51	5,905	53.49	11,040	100.00
Suspicious person(s)	6,013	46.36	6,958	53.64	12,971	100.00
Larceny	4,195	45.40	5,045	54.60	9,240	100.00
Shooting	2,561	45.73	3,039	54.27	5,600	100.00
Disturbance	37,478	45.26	45,335	54.74	82,813	100.00
Murder	274	48.41	292	51.59	566	100.00
Fire	1,957	57.22	1,463	42.78	3,420	100.00
Fight	10,316	49.02	10,729	50.98	21,045	100.00
Man on premises	8,140	45.38	9,796	54.62	17,936	100.00
Burglary	257	45.89	303	54.11	560	100.00
Wounding	3,286	51.81	3,056	48.19	6,342	100.00
Road Traffic Accident	12,522	48.97	13,051	51.03	25,573	100.00
Medical Emergency	13,485	84.66	2,443	15.34	15,928	100.00
Stolen Vehicle	4,255	58.49	3,020	41.51	7,275	100.00
Stone Throwing	3,828	48.63	4,043	51.37	7,871	100.00
Bomb scare	545	55.39	439	44.61	984	100.00
Malicious Damage	2,282	47.26	2,547	52.74	4,829	100.00
Alarm On	286	43.93	365	56.07	651	100.00
Armed With Weapon	6,063	49.53	6,178	50.47	12,241	100.00
Information	24,417	49.55	24,862	50.45	49,279	100.00
Kidnapping	330	52.38	300	47.62	630	100.00
Other Police	380	43.23	499	56.77	879	100.00

Call Description	Unmatched Count	Percent Unmatched	Matched Counts	Percent Matched	Total Counts	Percent Total
Fire involving overhead electrical lines	756	79.92	190	20.08	946	100.00
Bush, rubbish/tree fires	9,932	80.88	2,348	19.12	12,280	100.00
Fires at gas stations	15	88.24	2	11.76	17	100.00
Bomb threats/warning	987	80.11	245	19.89	1,232	100.00
Fire at wharehouses	30	76.92	9	23.08	39	100.00
Fire on vessels	16	69.57	7	30.43	23	100.00
Fire involving residential premises	1,839	77.66	529	22.34	2,368	100.00
Fire at commercial premises	492	78.34	136	21.66	628	100.00
Structural fires in high rise buildings	3	75.00	1	25.00	4	100.00
Fire in health care facility	13	86.67	2	13.33	15	100.00
Fire at oil installation	10	76.92	3	23.08	13	100.00
Fire at Preisdent/Prime minister	0	0.00	0	0.00	0	0.00
Fire at state prison	1	25.00	3	75.00	4	100.00
Fire at gov bldg, embassy, consulate, hc	78	78.00	22	22.00	100	100.00
Fire at educational institution	77	78.57	21	21.43	98	100.00
Fire at hotel/inn	15	88.24	2	11.76	17	100.00
Fire involving industrial plant (minor)	36	90.00	4	10.00	40	100.00
Fire involving industrial plant (major)	30	88.24	4	11.76	34	100.00
Road traffic accident 1 veh - NO FIRE	994	70.60	414	29.40	1,408	100.00
Road traffic accident 1 veh - WITH FIRE	215	75.70	69	24.30	284	100.00
Road traffic accident 2 veh- NO FIRE	470	68.21	219	31.79	689	100.00
Vehicle fire	383	72.40	146	27.60	529	100.00
Road traffic accident w/ multiple veh	63	80.77	15	19.23	78	100.00
Road traffic accident w/ gasoline truck	13	86.67	2	13.33	15	100.00
Road traffic accident w/ hazmat	5	83.33	1	16.67	6	100.00

Call Description	Unmatched Count	Percent Unmatched	Matched Counts	Percent Matched	Total Counts	Percent Total
Weather standby	0	0.00	3	100.00	3	100.00
Local standby	3	60.00	2	40.00	5	100.00
Domestic fire /other emergency	341	75.28	112	24.72	453	100.00
Aircraft accident imminent	4	100.00	0	0.00	4	100.00
Aircraft ground incident	2	100.00	0	0.00	2	100.00
Aircraft accidents	1	100.00	0	0.00	1	100.00
Full emergency	8	100.00	0	0.00	8	100.00
Rescue of trapped persons	73	74.49	25	25.51	98	100.00
Rescue from collapsed buildings	12	80.00	3	20.00	15	100.00
Rescue from floods	58	63.04	34	36.96	92	100.00
Special service	1,621	80.49	393	19.51	2,014	100.00
Suicide	460	50.77	446	49.23	906	100.00
Fire Alarm On	48	78.69	13	21.31	61	100.00
Leaking Hydrants	235	79.12	62	20.88	297	100.00
Information (Fire)	502	78.07	141	21.93	643	100.00
Armed With Fire-Arm/Ammunition	338	53.99	288	46.01	626	100.00
Total	232,744		203,917		436,661	

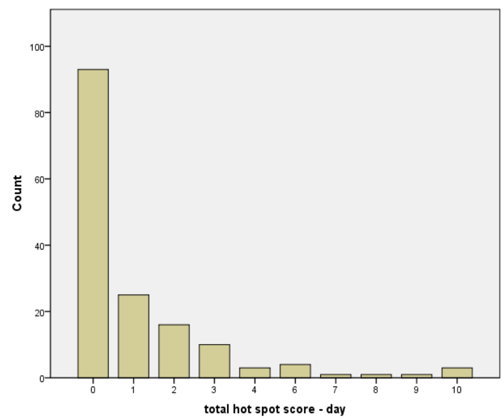
Comparison of E999 and Homicide Incident Report Locations



APPENDIX E

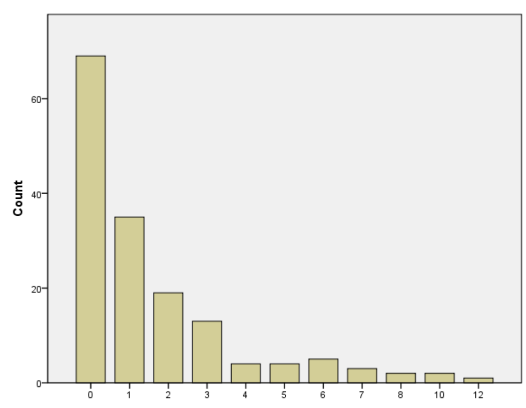
General Crime Hot Spot Day

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	93	59.2	59.2	59.2
	1	25	15.9	15.9	75.2
	2	16	10.2	10.2	85.4
	3	10	6.4	6.4	91.7
	4	3	1.9	1.9	93.6
	6	4	2.5	2.5	96.2
	7	1	.6	.6	96.8
	8	1	.6	.6	97.5
	9	1	.6	.6	98.1
	10	3	1.9	1.9	100.0
	Total	157	100.0	100.0	



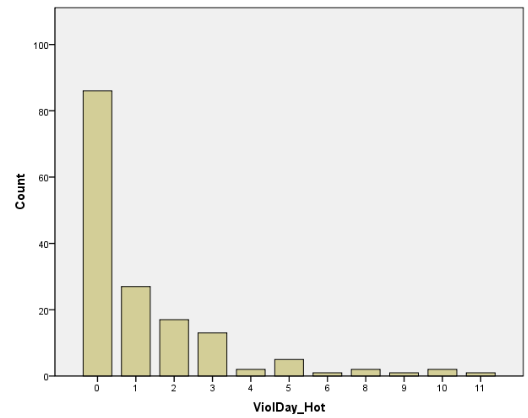
General Crime Hot Spot Night

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	69	43.9	43.9	43.9
	1	35	22.3	22.3	66.2
	2	19	12.1	12.1	78.3
	3	13	8.3	8.3	86.6
	4	4	2.5	2.5	89.2
	5	4	2.5	2.5	91.7
	6	5	3.2	3.2	94.9
	7	3	1.9	1.9	96.8
	8	2	1.3	1.3	98.1
	10	2	1.3	1.3	99.4
	12	1	.6	.6	100.0
	Total	157	100.0	100.0	



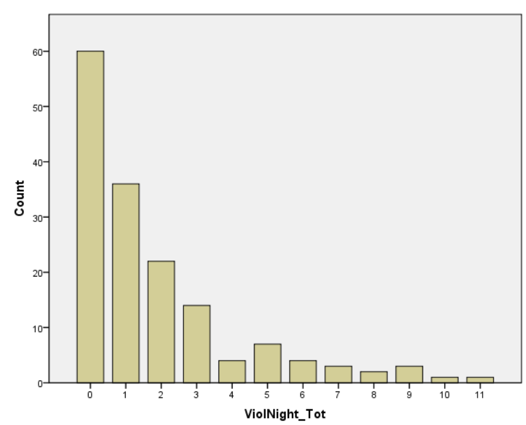
Violent Crime Hot Spot Day

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	86	54.8	54.8	54.8
	1	27	17.2	17.2	72.0
	2	17	10.8	10.8	82.8
	3	13	8.3	8.3	91.1
	4	2	1.3	1.3	92.4
	5	5	3.2	3.2	95.5
	6	1	.6	.6	96.2
	8	2	1.3	1.3	97.5
	9	1	.6	.6	98.1
	10	2	1.3	1.3	99.4
	11	1	.6	.6	100.0
	Total	157	100.0	100.0	



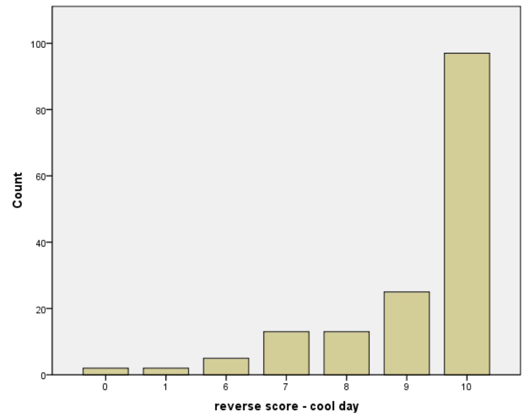
Violent Crime Hot Spot Night

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	60	38.2	38.2	38.2
	1	36	22.9	22.9	61.1
	2	22	14.0	14.0	75.2
	3	14	8.9	8.9	84.1
	4	4	2.5	2.5	86.6
	5	7	4.5	4.5	91.1
	6	4	2.5	2.5	93.6
	7	3	1.9	1.9	95.5
	8	2	1.3	1.3	96.8
	9	3	1.9	1.9	98.7
	10	1	.6	.6	99.4
	11	1	.6	.6	100.0
	Total	157	100.0	100.0	



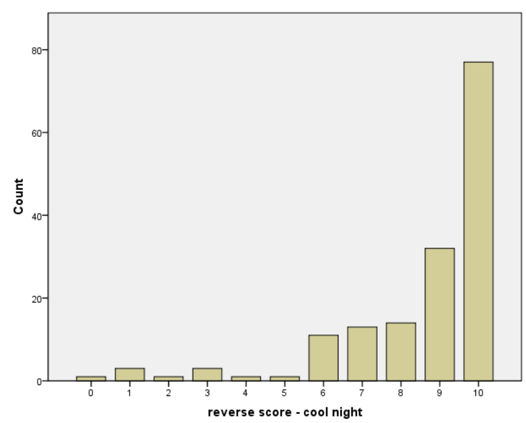
Cool Spot Day

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	2	1.3	1.3	1.3
	1	2	1.3	1.3	2.5
	6	5	3.2	3.2	5.7
	7	13	8.3	8.3	14.0
	8	13	8.3	8.3	22.3
	9	25	15.9	15.9	38.2
	10	97	61.8	61.8	100.0
	Total	157	100.0	100.0	



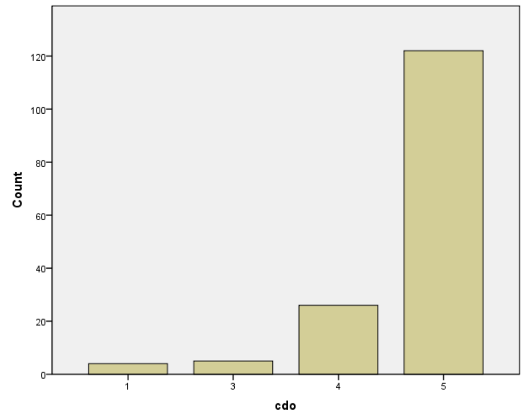
Cool Spot Night

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	1	.6	.6	.6
	1	3	1.9	1.9	2.5
	2	1	.6	.6	3.2
	3	3	1.9	1.9	5.1
	4	1	.6	.6	5.7
	5	1	.6	.6	6.4
	6	11	7.0	7.0	13.4
	7	13	8.3	8.3	21.7
	8	14	8.9	8.9	30.6
	9	32	20.4	20.4	51.0
	10	77	49.0	49.0	100.0
	Total	157	100.0	100.0	



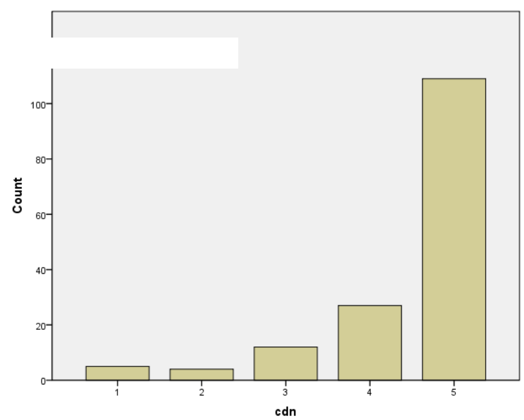
Cool Spot Day – Recoded Ordinal

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	4	2.5	2.5	2.5
	3	5	3.2	3.2	5.7
	4	26	16.6	16.6	22.3
	5	122	77.7	77.7	100.0
	Total	157	100.0	100.0	



Cool Spot Night – Recoded Ordinal

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	5	3.2	3.2	3.2
	2	4	2.5	2.5	5.7
	3	12	7.6	7.6	13.4
	4	27	17.2	17.2	30.6
	5	109	69.4	69.4	100.0
	Total	157	100.0	100.0	



APPENDIX F

Correlations Matrix for Independent Variables

	q_61	q_62	Eth_re~e	Educ_R~e	Marita~e	crime_~3	crime_59	PHYsco~r	SOCdis~1	q_6	FAMscore	q_69	PercMa~t
q_61	1.0000												
q_62	0.1526	1.0000											
Eth_recode	-0.0347	-0.0285	1.0000										
Educ_Recode	-0.2263	-0.0259	-0.1170	1.0000									
Marital_Re~e	0.5071	0.3158	-0.0752	0.0413	1.0000								
crime_top3	-0.0593	-0.0621	0.1487	0.0421	-0.0534	1.0000							
crime_59	-0.0383	0.0909	0.1680	0.0422	-0.0590	-0.0311	1.0000						
PHYscorePr	-0.1791	-0.0194	0.0997	0.1212	-0.1147	0.1290	0.1674	1.0000					
SOCdisSC_1	-0.3170	-0.0517	0.0353	0.1133	-0.1531	0.3115	-0.0045	0.5446	1.0000				
q_6	0.5130	-0.0647	-0.0975	-0.2052	0.1716	-0.0739	-0.0824	-0.1489	-0.2033	1.0000			
FAMscore	-0.1135	0.0597	-0.2033	-0.0675	-0.0962	-0.0237	0.0081	-0.1314	-0.0124	-0.0147	1.0000		
q_69	-0.2177	-0.1993	0.1119	0.1046	-0.1142	0.0021	-0.0472	-0.0122	0.0653	-0.2615	0.0608	1.0000	
PercMapNight	0.1042	0.0601	0.0354	-0.0586	0.0547	0.0172	0.0618	-0.0008	-0.0878	0.0668	0.0129	-0.0032	1.0000

VIF and Tolerance Statistics for Independent Variables

Variable	VIF	Tolerance ($1-R_X^2$)
Gender	2.02	0.494270
Social Disorder	1.72	0.582807
Physical Disorder	1.55	0.646887
Marital Status	1.55	0.647026
Length of Residency	1.51	0.661217
Age	1.22	0.819199
Number of Days Outside Neighborhood	1.17	0.852401
Ethnicity	1.17	0.853707
Education	1.16	0.863828
Crime is a Top 3 Problem	1.15	0.866141
Familiarity Score	1.12	0.890684
Crime is a Problem in Neighborhood	1.10	0.906453
Percent Map Marked Night	1.03	0.970843

APPENDIX G

Model 1Diagnositcs - General Crime Hot Spot Day

Parameter Estimates for Estimated Models, General Crime Hot Spots Day

Variable	PRM	NBRM	ZIP
TotHotDay			
respondent age	1.014	1.010	1.019
	1.33	0.70	1.53
respondent gender	0.794	0.702	0.750
	-1.18	-1.26	-1.45
ethnicity dichotomous recode	1.304	1.180	1.147
	1.37	0.63	0.64
education recoded	1.292	1.236	1.212
	2.38	1.47	1.79
marital status recode	0.998	1.042	0.915
	-0.01	0.25	-0.66
physical disorder proportion~o	1.040	0.981	1.111
	0.19	-0.07	0.48
corrected social disorder pr~r	1.559	1.602	1.329
	2.36	1.85	1.34
identified crime as a reason~	1.639	1.488	1.329
	2.36	1.46	1.39
how long have you lived in y~	0.999	0.999	0.999
	-1.05	-1.02	-1.55
neighborhood familiarity score	1.859	1.660	1.658
	3.74	2.47	2.77
sum square feet of marked ar~	1.000	1.000	1.000
	14.34	6.56	9.68
Constant	0.010	0.024	0.063
	-4.66	-2.99	-2.67
lnalpha			
Constant		0.604	
		-1.23	
inflate			
neighborhood familiarity score			0.838
			-0.33
sum square feet of marked ar~			1.000
			-1.79
Constant			9.587
			1.23
Statistics			
alpha		0.604	
N	152	152	152
ll	-193.627	-185.614	-160.802
bic	447.540	436.539	396.962
aic	411.253	397.228	351.604

legend: b/t

Comparison of Mean Observed and Predicted Counts, General Crime Hot Spots Day

Model	Maximum Difference	At Value	Mean |Diff|
PRM	-0.139	1	0.034
NBRM	-0.083	1	0.019
ZIP	-0.019	5	0.008

Predicted and Actual Probabilities for Estimated Models, General Crime Hot Spots Day

PRM: Predicted and actual probabilities

Count	Actual	Predicted	|Diff|	Pearson
0	0.586	0.466	0.120	4.663
1	0.158	0.296	0.139	9.841
2	0.105	0.129	0.024	0.661
3	0.066	0.050	0.016	0.770
4	0.020	0.019	0.000	0.001
5	0.000	0.009	0.009	1.310
6	0.026	0.005	0.021	13.713
7	0.007	0.004	0.003	0.312
8	0.007	0.003	0.003	0.538
9	0.007	0.003	0.004	0.793
Sum	0.980	0.984	0.338	32.602

NBRM: Predicted and actual probabilities

Count	Actual	Predicted	|Diff|	Pearson
0	0.586	0.547	0.039	0.418
1	0.158	0.240	0.083	4.311
2	0.105	0.100	0.005	0.045
3	0.066	0.044	0.022	1.649
4	0.020	0.021	0.001	0.013
5	0.000	0.011	0.011	1.683
6	0.026	0.006	0.020	9.425
7	0.007	0.004	0.003	0.237
8	0.007	0.003	0.004	0.763
9	0.007	0.002	0.004	1.433
Sum	0.980	0.979	0.192	19.977

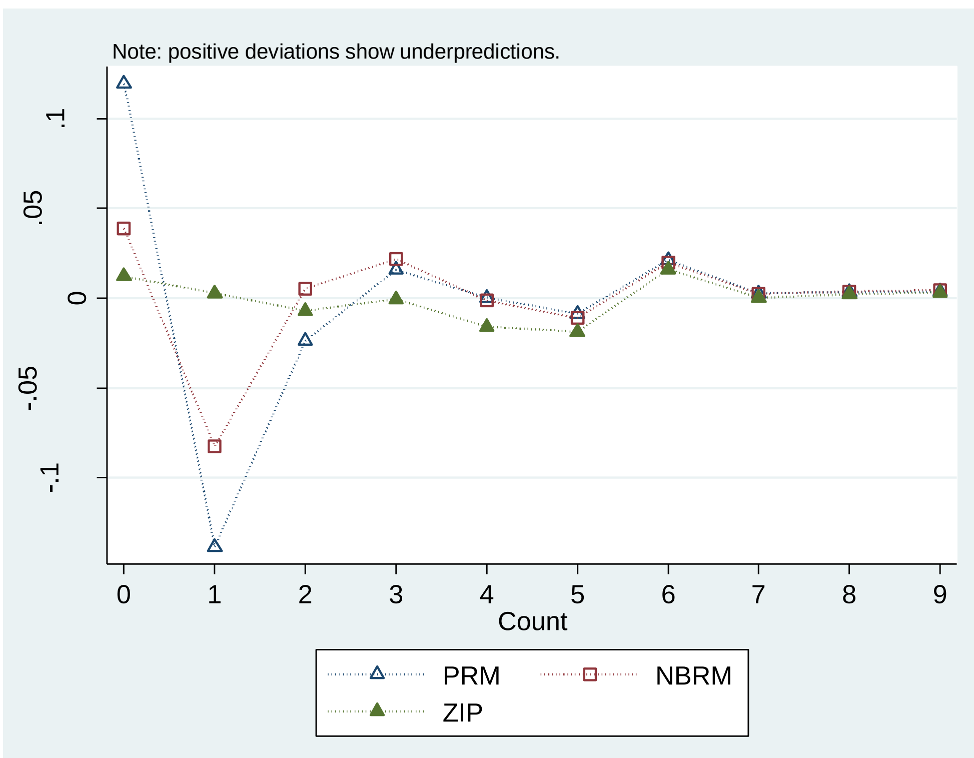
ZIP: Predicted and actual probabilities

Count	Actual	Predicted	|Diff|	Pearson
0	0.586	0.573	0.012	0.040
1	0.158	0.155	0.003	0.007
2	0.105	0.112	0.007	0.066
3	0.066	0.066	0.000	0.000
4	0.020	0.036	0.016	1.070
5	0.000	0.019	0.019	2.834
6	0.026	0.010	0.016	3.822
7	0.007	0.006	0.000	0.002
8	0.007	0.004	0.002	0.162
9	0.007	0.003	0.003	0.450
Sum	0.980	0.985	0.079	8.453

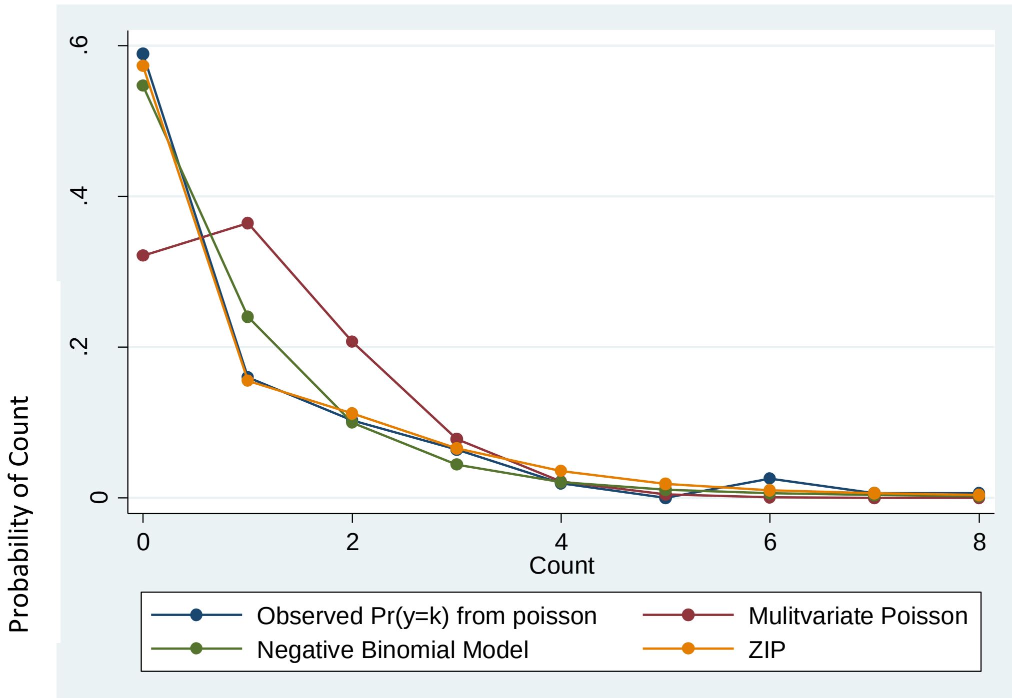
Test and Fit Statistics, General Crime Hot Spots Day

```
PRM            BIC=  -316.090  AIC=     2.706  Prefer  Over   Evidence
-------------------------------------------------------------------------
  vs NBRM      BIC=  -327.091  dif=    11.001  NBRM    PRM    Very strong
               AIC=     2.613  dif=     0.092  NBRM    PRM
               LRX2=   16.025  prob=    0.000  NBRM    PRM    p=0.000
-------------------------------------------------------------------------
  vs ZIP       BIC=  -366.668  dif=    50.577  ZIP     PRM    Very strong
               AIC=     2.313  dif=     0.392  ZIP     PRM
               Vuong=   4.175  prob=    0.000  ZIP     PRM    p=0.000
-------------------------------------------------------------------------
NBRM           BIC=  -327.091  AIC=     2.613  Prefer  Over   Evidence
-------------------------------------------------------------------------
  vs ZIP       BIC=  -366.668  dif=    39.577  ZIP     NBRM   Very strong
               AIC=     2.313  dif=     0.300  ZIP     NBRM
-------------------------------------------------------------------------
ZIP            BIC=  -366.668  AIC=     2.313  Prefer  Over   Evidence
```

Residual Plot for Estimated Models, General Crime Hot Spots Day



Prcounts Plot for Estimated Models, General Crime Hot Spots Day



Model 2 Diagnostics - General Crime Hot Spot Night

Parameter Estimates for Estimated Models, General Crime Hot Spots Night

Variable	PRM	NBRM	ZIP	ZINB
TotalHotN				
respondent age	1.004	1.001	1.004	1.001
	0.42	0.05	0.38	0.09
respondent gender	0.840	0.801	0.660	0.758
	-1.06	-0.95	-2.32	-1.29
ethnicity dichotomous recode	1.358	1.331	1.176	1.257
	1.89	1.27	0.88	1.07
education recoded	1.057	1.112	1.076	1.087
	0.57	0.83	0.74	0.69
marital status recode	1.078	1.137	1.110	1.117
	0.77	0.99	0.99	0.88
physical disorder proportion~o	1.121	0.991	0.975	1.062
	0.63	-0.03	-0.12	0.24
corrected social disorder pr~r	1.355	1.275	1.341	1.211
	1.94	1.14	1.56	0.93
identified crime as a reason~	1.211	0.995	0.808	0.976
	1.14	-0.02	-1.19	-0.12
how long have you lived in y~	1.000	1.000	1.000	1.000
	-0.34	-0.13	0.48	-0.05
neighborhood familiarity score	1.725	1.644	1.329	1.487
	4.09	2.90	1.88	2.41
PercMapNight	1.033	1.047	1.036	1.035
	12.64	6.97	9.84	6.09
Constant	0.039	0.058	0.280	0.142
	-3.92	-2.68	-1.39	-1.92
lnalpha				
Constant		0.508		0.283
		-2.24		-3.18
inflate				
neighborhood familiarity score			0.620	0.813
			-1.27	-0.37
PercMapNight			0.950	0.207
			-1.84	-1.81
Constant			2.779	4.756
			0.80	0.86
Statistics				
alpha		0.508		
N	152	152	152	152
ll	-239.434	-221.900	-213.570	-213.723
bic	539.156	509.110	502.497	507.827
aic	502.869	469.799	457.139	459.445

legend: b/t

Comparison of Mean Observed and Predicted Counts, General Crime Hot Spots Night

Model	Maximum Difference	At Value	Mean |Diff|
PRM	0.117	0	0.033
NBRM	-0.038	1	0.014
ZIP	0.030	1	0.013
ZINB	0.019	6	0.011

Predicted or Actual Probabilities for Estimated Models, General Crime Hot Spots Night

PRM: Predicted and actual probabilities

Count	Actual	Predicted	|Diff|	Pearson
0	0.447	0.330	0.117	6.293
1	0.224	0.311	0.087	3.696
2	0.118	0.181	0.062	3.281
3	0.086	0.087	0.001	0.003
4	0.026	0.039	0.012	0.595
5	0.020	0.017	0.003	0.056
6	0.033	0.008	0.024	10.673
7	0.020	0.005	0.015	6.277
8	0.013	0.004	0.009	3.284
9	0.000	0.003	0.003	0.521
Sum	0.987	0.986	0.334	34.679

NBRM: Predicted and actual probabilities

Count	Actual	Predicted	|Diff|	Pearson
0	0.447	0.434	0.014	0.064
1	0.224	0.261	0.038	0.828
2	0.118	0.132	0.014	0.212
3	0.086	0.066	0.020	0.886
4	0.026	0.034	0.008	0.281
5	0.020	0.019	0.001	0.005
6	0.033	0.011	0.022	6.356
7	0.020	0.007	0.013	3.382
8	0.013	0.005	0.008	2.166
9	0.000	0.003	0.003	0.531
Sum	0.987	0.973	0.139	14.711

ZIP: Predicted and actual probabilities

Count	Actual	Predicted	|Diff|	Pearson
0	0.447	0.454	0.007	0.016
1	0.224	0.194	0.030	0.698
2	0.118	0.146	0.027	0.766
3	0.086	0.085	0.000	0.000
4	0.026	0.045	0.018	1.159
5	0.020	0.023	0.003	0.076
6	0.033	0.013	0.020	4.953
7	0.020	0.008	0.012	2.903
8	0.013	0.005	0.008	1.801
9	0.000	0.004	0.004	0.615
Sum	0.987	0.976	0.130	12.988

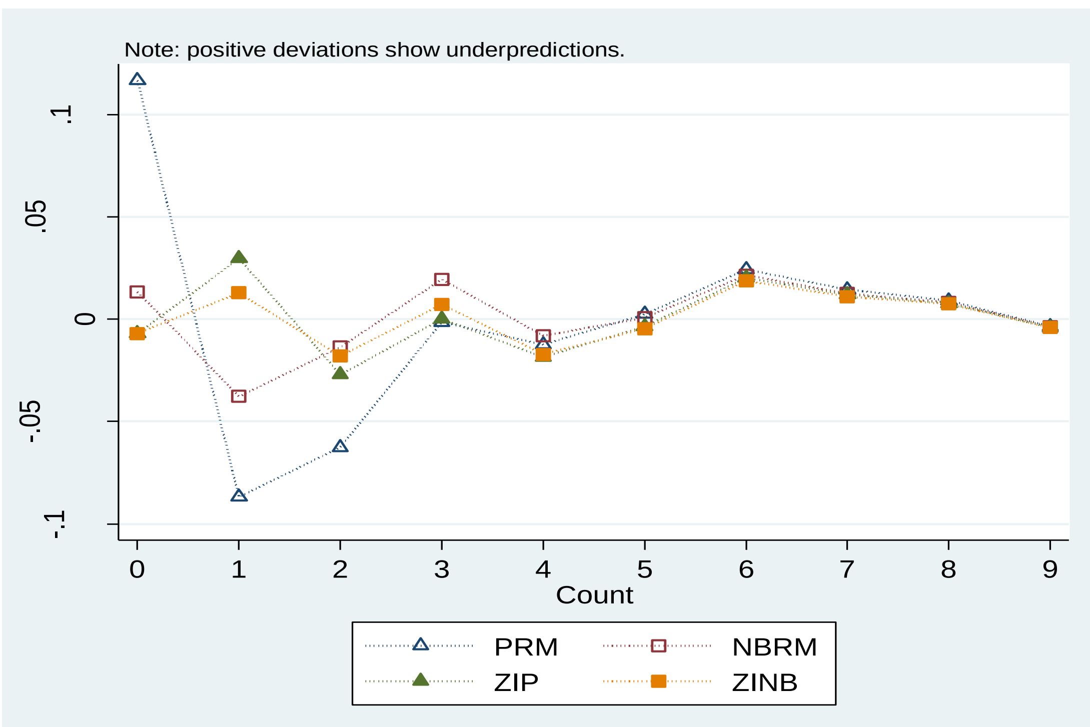
ZINB: Predicted and actual probabilities

Count	Actual	Predicted	|Diff|	Pearson
0	0.447	0.454	0.007	0.016
1	0.224	0.211	0.013	0.120
2	0.118	0.136	0.018	0.357
3	0.086	0.078	0.007	0.105
4	0.026	0.043	0.017	1.016
5	0.020	0.024	0.005	0.128
6	0.033	0.014	0.019	3.818
7	0.020	0.009	0.011	2.168
8	0.013	0.006	0.008	1.520
9	0.000	0.004	0.004	0.598
Sum	0.987	0.979	0.108	9.846

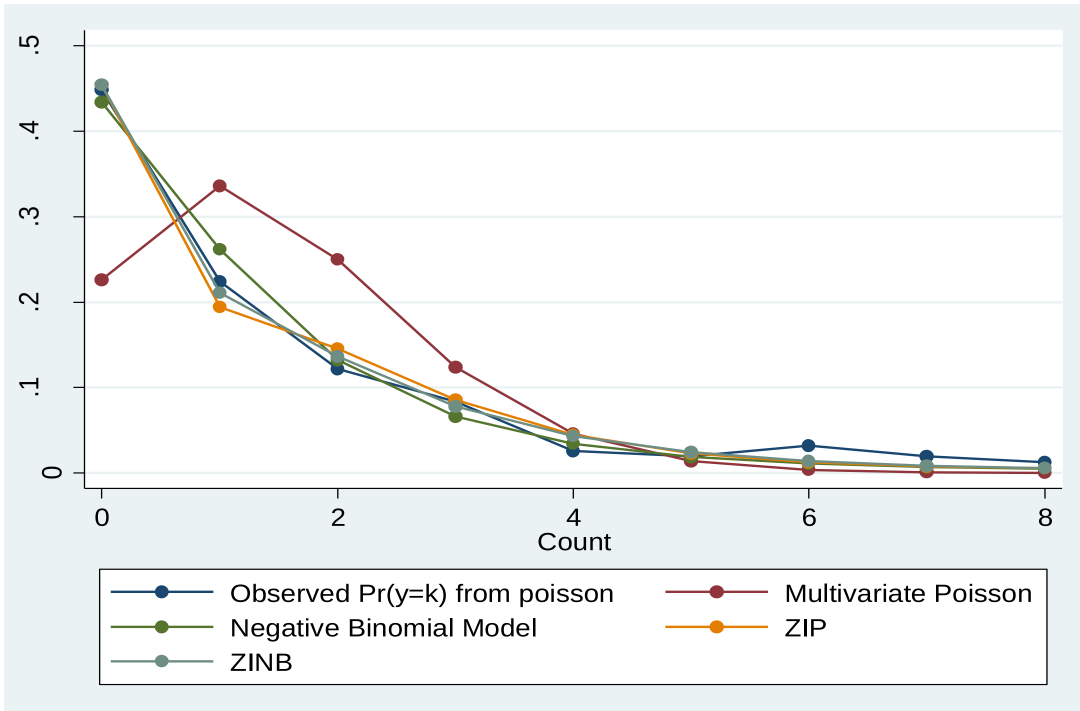
Test and Fit Statistics, General Crime Hot Spots Night

PRM	BIC=	-224.474	AIC=	3.308	Prefer	Over	Evidence
vs NBRM	BIC=	-254.520	dif=	30.046	NBRM	PRM	Very strong
	AIC=	3.091	dif=	0.218	NBRM	PRM	
	LRX2=	35.070	prob=	0.000	NBRM	PRM	p=0.000
vs ZIP	BIC=	-261.132	dif=	36.658	ZIP	PRM	Very strong
	AIC=	3.007	dif=	0.301	ZIP	PRM	
	Vuong=	2.619	prob=	0.004	ZIP	PRM	p=0.004
vs ZINB	BIC=	-255.802	dif=	31.328	ZINB	PRM	Very strong
	AIC=	3.023	dif=	0.286	ZINB	PRM	
NBRM	BIC=	-254.520	AIC=	3.091	Prefer	Over	Evidence
vs ZIP	BIC=	-261.132	dif=	6.612	ZIP	NBRM	Strong
	AIC=	3.007	dif=	0.083	ZIP	NBRM	
vs ZINB	BIC=	-255.802	dif=	1.282	ZINB	NBRM	Weak
	AIC=	3.023	dif=	0.068	ZINB	NBRM	
	Vuong=	1.952	prob=	0.025	ZINB	NBRM	p=0.025
ZIP	BIC=	-261.132	AIC=	3.007	Prefer	Over	Evidence
vs ZINB	BIC=	-255.802	dif=	-5.330	ZIP	ZINB	Positive
	AIC=	3.023	dif=	-0.015	ZIP	ZINB	
	LRX2=	0.306	prob=	0.290	ZINB	ZIP	p=0.000

Residual Plot for Each Estimated Model, General Crime Hot Spots Night



Prcounts for Estimated Models, General Crime Hot Spots Night



Model 3 Diagnostics - Violent Crime Hot Spots Day

Parameter Estimates for Estimated Models, Violent Crime Hot Spots Day

Variable	PRM	NBRM	ZIP
ViolDay_Hot			
respondent age	1.002	0.997	1.012
	0.16	-0.25	0.95
respondent gender	0.684	0.693	0.736
	-1.84	-1.36	-1.44
ethnicity dichotomous recode	1.209	1.256	1.196
	1.01	0.90	0.85
education recoded	1.044	0.977	1.056
	0.38	-0.17	0.46
marital status recode	1.082	1.109	0.977
	0.71	0.71	-0.19
identified crime as a reason~	1.495	1.335	1.343
	2.00	1.16	1.44
is crime named as one of the~p	0.903	0.939	0.890
	-0.60	-0.27	-0.64
physical disorder proportion~o	0.947	0.983	0.951
	-0.28	-0.06	-0.24
corrected social disorder pr~r	1.702	1.680	1.534
	2.90	2.18	2.06
how long have you lived in y~	1.000	1.000	1.000
	-0.63	-0.25	-0.28
neighborhood familiarity score	1.758	1.637	1.630
	3.62	2.66	3.00
respondent number of days/we~l	0.975	0.962	0.993
	-0.55	-0.62	-0.14
PerMapDay	1.038	1.048	1.029
	14.22	6.86	9.03
Constant	0.044	0.063	0.086
	-3.19	-2.30	-2.37
lnalpha			
Constant		0.447	
		-1.80	
inflate			
PerMapNight			0.523
			-1.81
Constant			4.239
			2.94
Statistics			
alpha		0.447	
N	152	152	152
ll	-198.726	-193.636	-172.663
bic	467.787	462.630	425.707
aic	425.452	417.272	377.325

legend: b/t

Comparison of Mean Observed and Predicted Counts, Violent Crime Hot Spot Day

Model	Maximum Difference	At Value	Mean |Diff|
PRM	-0.135	1	0.037
NBRM	-0.089	1	0.023
ZIP	-0.022	4	0.011

Predicted and Actual Probabilities for each Estimated Model, Violent Crime Hot Spots Day

PRM: Predicted and actual probabilities

Count	Actual	Predicted	|Diff|	Pearson
0	0.546	0.431	0.115	4.667
1	0.171	0.306	0.135	9.089
2	0.105	0.142	0.037	1.439
3	0.086	0.057	0.029	2.217
4	0.013	0.022	0.009	0.564
5	0.033	0.009	0.024	9.233
6	0.007	0.004	0.002	0.169
7	0.000	0.003	0.003	0.409
8	0.013	0.002	0.011	7.785
9	0.007	0.002	0.004	1.078
Sum	0.980	0.979	0.368	36.651

NBRM: Predicted and actual probabilities

Count	Actual	Predicted	|Diff|	Pearson
0	0.546	0.502	0.044	0.577
1	0.171	0.260	0.089	4.611
2	0.105	0.114	0.008	0.091
3	0.086	0.050	0.036	3.872
4	0.013	0.023	0.010	0.670
5	0.033	0.012	0.021	5.697
6	0.007	0.007	0.000	0.000
7	0.000	0.004	0.004	0.619
8	0.013	0.003	0.010	5.981
9	0.007	0.002	0.005	1.563
Sum	0.980	0.976	0.227	23.681

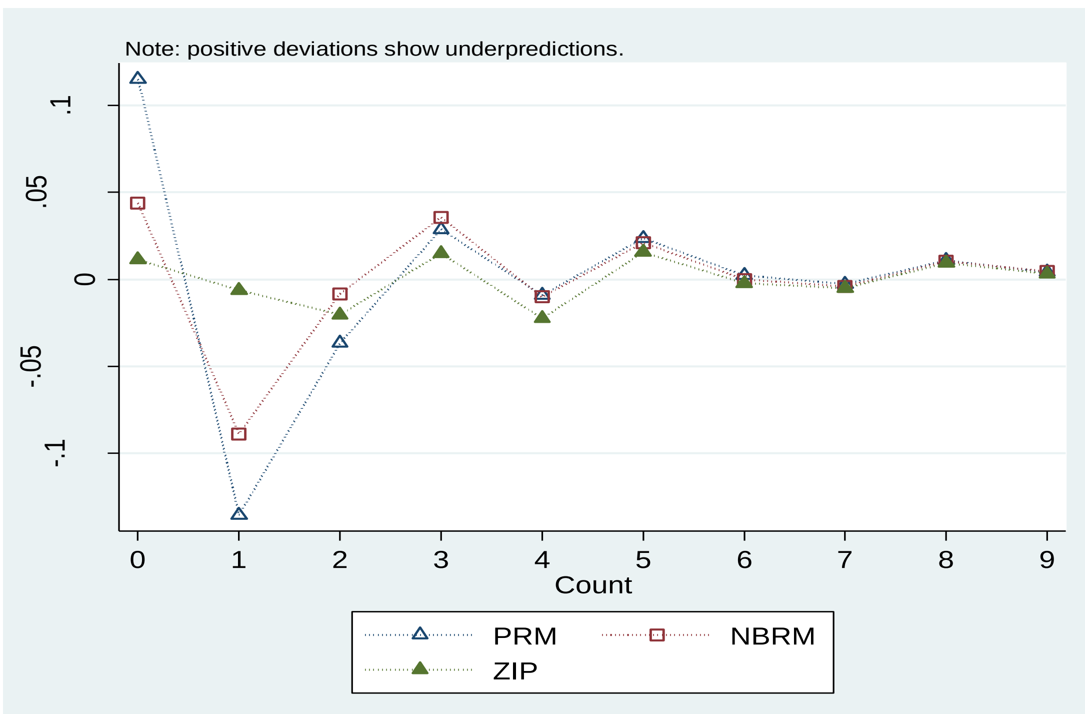
ZIP: Predicted and actual probabilities

Count	Actual	Predicted	|Diff|	Pearson
0	0.546	0.535	0.011	0.036
1	0.171	0.177	0.006	0.032
2	0.105	0.126	0.020	0.497
3	0.086	0.071	0.015	0.477
4	0.013	0.036	0.022	2.149
5	0.033	0.017	0.016	2.132
6	0.007	0.009	0.002	0.083
7	0.000	0.005	0.005	0.780
8	0.013	0.004	0.009	3.541
9	0.007	0.003	0.003	0.468
Sum	0.980	0.982	0.111	10.196

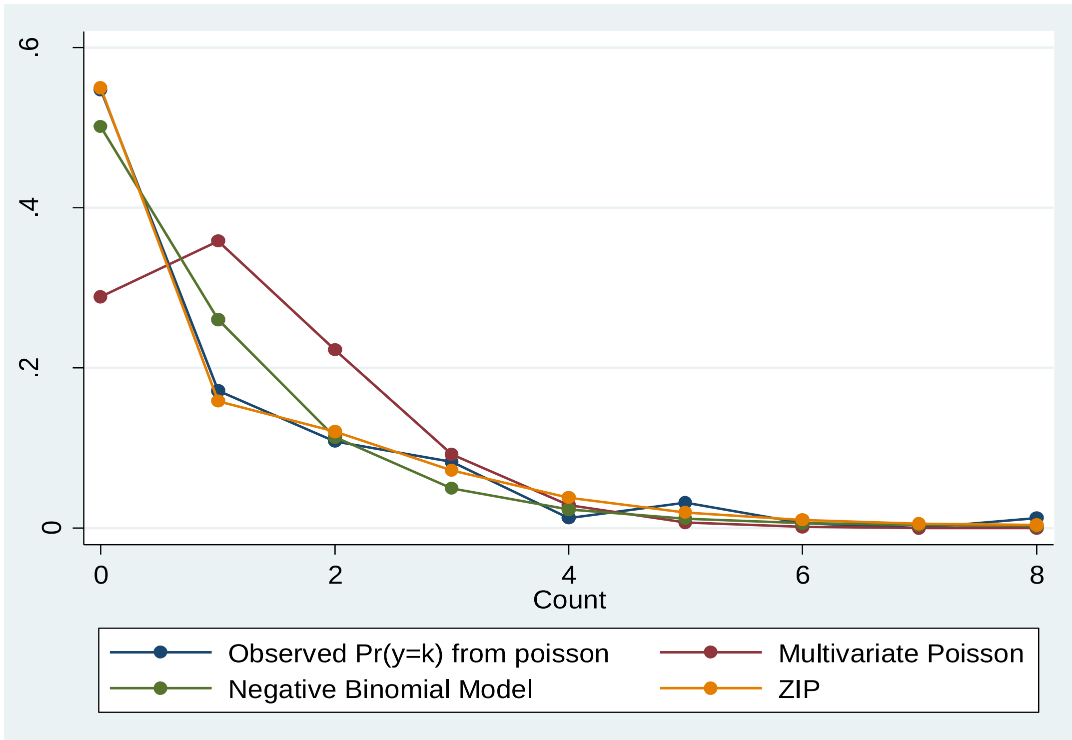
Test and Fit Statistics, Violent Crime Hot Spot Day

PRM	BIC=	-295.843	AIC=	2.799	Prefer	Over	Evidence
vs NBRM	BIC=	-300.999	dif=	5.156	NBRM	PRM	Positive
	AIC=	2.745	dif=	0.054	NBRM	PRM	
	LRX2=	10.180	prob=	0.001	NBRM	PRM	p=0.001
vs ZIP	BIC=	-337.923	dif=	42.080	ZIP	PRM	Very strong
	AIC=	2.482	dif=	0.317	ZIP	PRM	
	Vuong=	3.445	prob=	0.000	ZIP	PRM	p=0.000
NBRM	BIC=	-300.999	AIC=	2.745	Prefer	Over	Evidence
vs ZIP	BIC=	-337.923	dif=	36.923	ZIP	NBRM	Very strong
	AIC=	2.482	dif=	0.263	ZIP	NBRM	
ZIP	BIC=	-337.923	AIC=	2.482	Prefer	Over	Evidence

Residual Plot for Estimated Models, Violent Crime Hot Spot Day



Prcounts Plot for Estimated Models, Violent Crime Hot Spot Day



Model 4 Diagnostics - Violent Crime Hot Spots Night

Parameter Estimates for Estimated Models, Violent Crime Hot Spots Night

Variable	PRM	NBRM	ZIP
ViolNight_Tot			
respondent age	0.996	0.994	1.003
	-0.54	-0.67	0.28
respondent gender	0.667	0.691	0.653
	-2.39	-1.85	-2.44
ethnicity dichotomous recode	1.083	1.066	1.019
	0.51	0.35	0.12
education recoded	0.964	0.980	0.955
	-0.40	-0.20	-0.50
marital status recode	1.212	1.192	1.188
	2.23	1.75	1.85
identified crime as a reason~	1.086	1.020	1.024
	0.53	0.11	0.15
is crime named as one of the~p	1.291	1.170	1.133
	1.73	0.89	0.81
physical disorder proportion~o	1.121	1.125	1.068
	0.67	0.57	0.37
corrected social disorder pr~r	1.194	1.222	1.292
	1.13	1.11	1.48
how long have you lived in y~	1.000	1.000	1.000
	0.41	0.76	0.34
neighborhood familiarity score	1.551	1.534	1.421
	3.66	3.17	2.99
respondent number of days/we~l	0.996	1.002	0.984
	-0.10	0.04	-0.41
PerMapNight	1.033	1.038	1.026
	14.81	9.28	10.93
Constant	0.153	0.146	0.318
	-2.42	-2.17	-1.46
lnalpha			
Constant		0.165	
		-3.29	
inflate			
PerMapNight			0.271
			-2.94
Constant			3.827
			2.75
Statistics			
alpha		0.165	
N	152	152	152
ll	-231.749	-228.902	-205.606
bic	533.832	533.163	491.594
aic	491.498	487.804	443.212

legend: b/t

Comparison of Mean Observed and Predicted Counts, Violent Crime Hot Spot Night

Model	Maximum Difference	At Value	Mean |Diff|
PRM	0.084	0	0.029
NBRM	-0.052	1	0.021
ZIP	0.059	1	0.019

Predicted and Actual Probabilities for Estimated Models, Violent Crime Hot Spot Night

PRM: Predicted and actual probabilities

Count	Actual	Predicted	|Diff|	Pearson
0	0.375	0.291	0.084	3.678
1	0.237	0.303	0.066	2.169
2	0.145	0.190	0.045	1.648
3	0.092	0.097	0.005	0.043
4	0.020	0.046	0.027	2.341
5	0.046	0.023	0.023	3.674
6	0.020	0.012	0.008	0.742
7	0.020	0.007	0.012	3.191
8	0.013	0.005	0.008	1.948
9	0.020	0.004	0.016	9.846
Sum	0.987	0.979	0.294	29.279

NBRM: Predicted and actual probabilities

Count	Actual	Predicted	|Diff|	Pearson
0	0.375	0.333	0.042	0.810
1	0.237	0.289	0.052	1.435
2	0.145	0.168	0.024	0.505
3	0.092	0.086	0.006	0.057
4	0.020	0.044	0.024	1.978
5	0.046	0.023	0.023	3.578
6	0.020	0.013	0.007	0.543
7	0.020	0.008	0.012	2.604
8	0.013	0.005	0.008	1.675
9	0.020	0.004	0.016	9.573
Sum	0.987	0.973	0.213	22.759

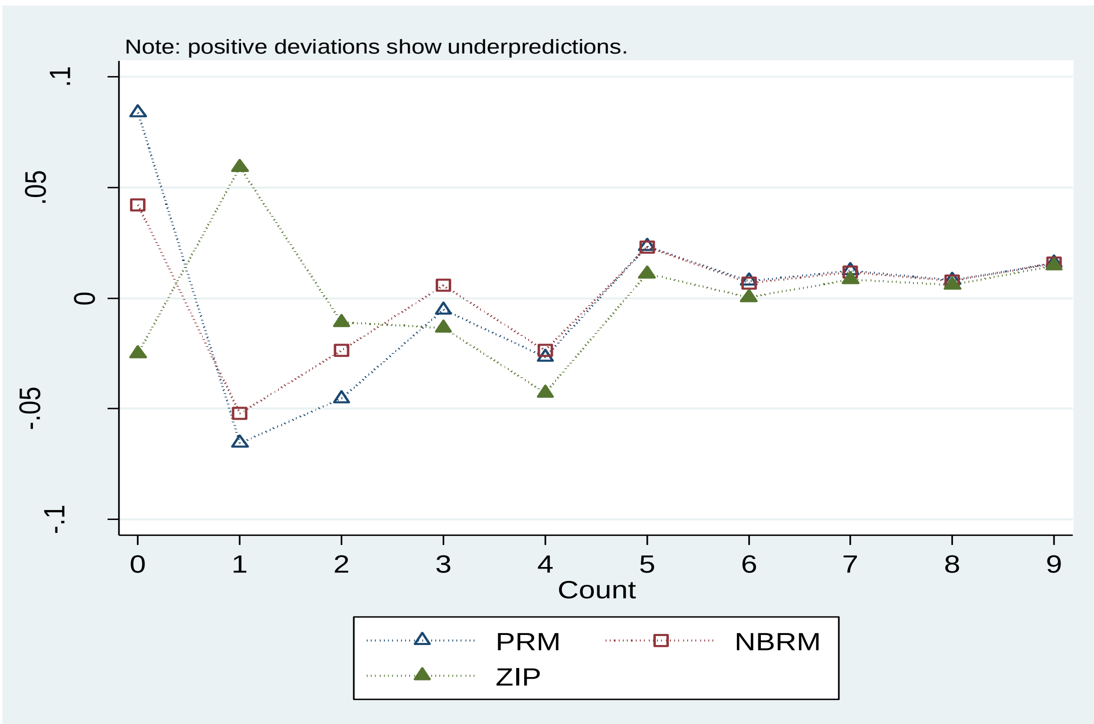
ZIP: Predicted and actual probabilities

Count	Actual	Predicted	|Diff|	Pearson
0	0.375	0.400	0.025	0.239
1	0.237	0.178	0.059	3.003
2	0.145	0.156	0.011	0.118
3	0.092	0.106	0.014	0.263
4	0.020	0.063	0.043	4.469
5	0.046	0.035	0.011	0.534
6	0.020	0.019	0.000	0.001
7	0.020	0.011	0.008	0.946
8	0.013	0.007	0.006	0.743
9	0.020	0.005	0.015	6.470
Sum	0.987	0.980	0.192	16.786

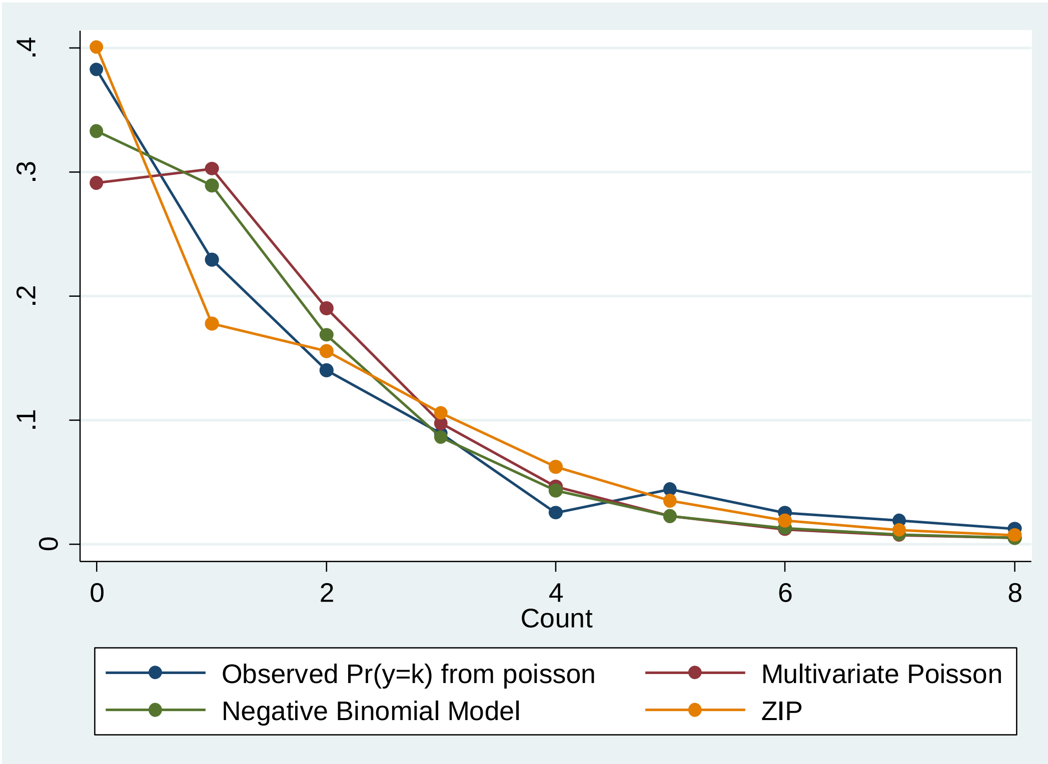
Test and Fit Statistics, Violent Crime Hot Spots Night

PRM	BIC=	-229.797	AIC=	3.234	Prefer	Over	Evidence
vs NBRM	BIC=	-230.467	dif=	0.670	NBRM	PRM	Weak
	AIC=	3.209	dif=	0.024	NBRM	PRM	
	LRX2=	5.694	prob=	0.009	NBRM	PRM	p=0.009
vs ZIP	BIC=	-272.036	dif=	42.238	ZIP	PRM	Very strong
	AIC=	2.916	dif=	0.318	ZIP	PRM	
	Vuong=	3.438	prob=	0.000	ZIP	PRM	p=0.000
NBRM	BIC=	-230.467	AIC=	3.209	Prefer	Over	Evidence
vs ZIP	BIC=	-272.036	dif=	41.568	ZIP	NBRM	Very strong
	AIC=	2.916	dif=	0.293	ZIP	NBRM	
ZIP	BIC=	-272.036	AIC=	2.916	Prefer	Over	Evidence

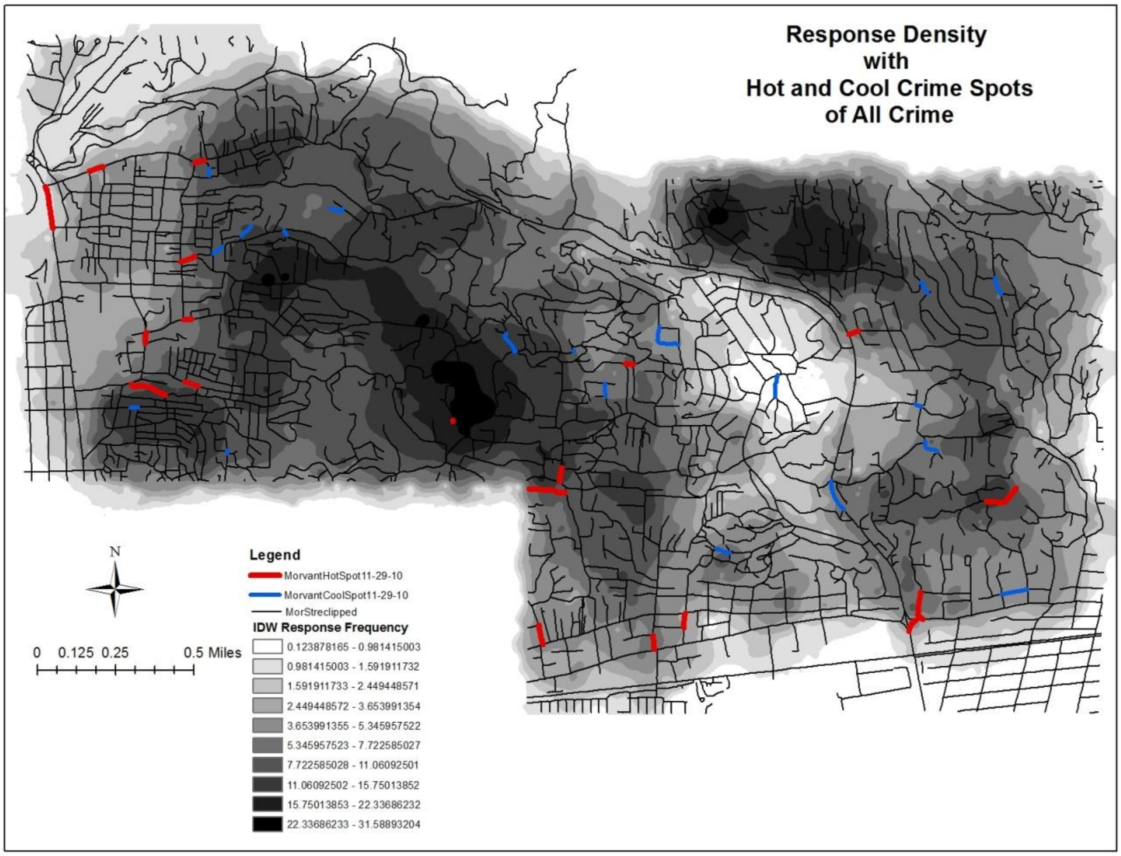
Residual Plot for Estimated Models, Violent Crime Hot Spot Night

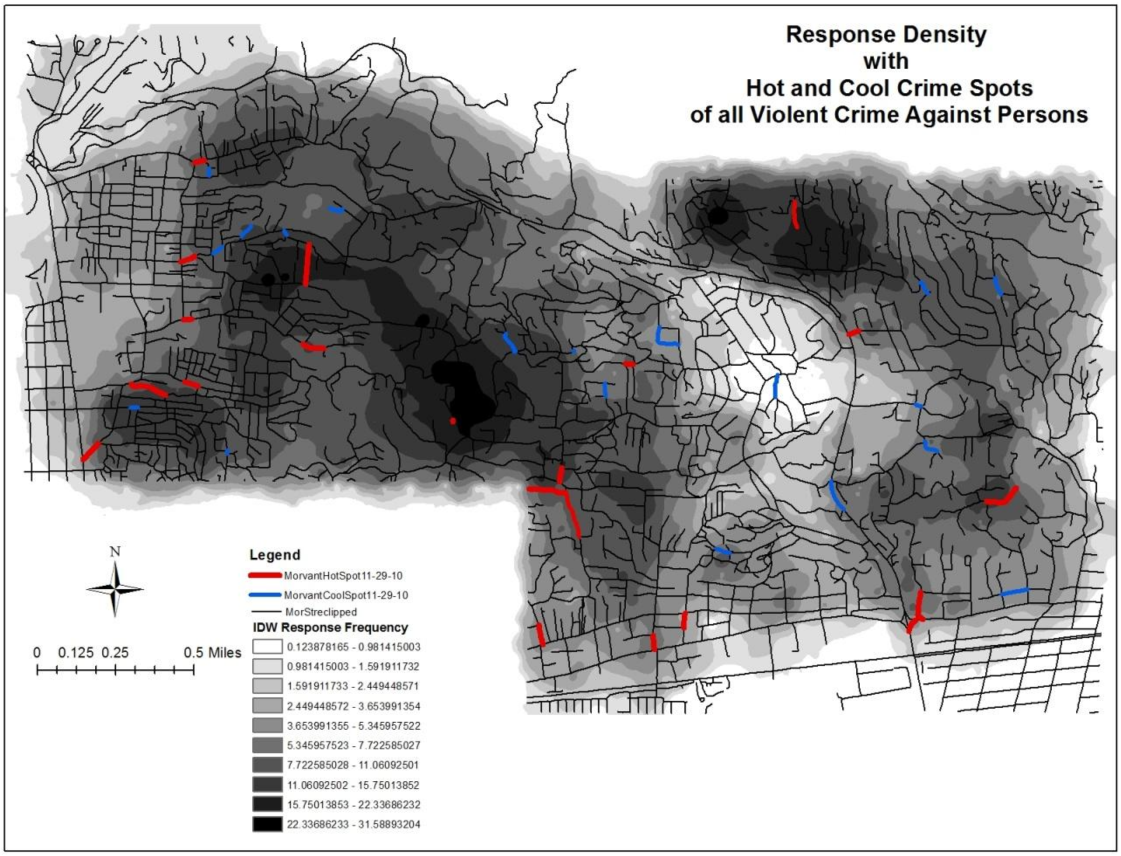


Prcounts Plot for Estimated Models, Violent Crime Hot Spot Night



APPENDIX H


Response Density
with
Hot and Cool Crime Spots
of All Crime
N
0 0.125 0.25 0.5 Miles
Legend
MorvantHotSpot11-29-10
MorvantCoolSpot11-29-10
MorStreclipped
IDW Response Frequency
0.123878165 - 0.981415003
0.981415003 - 1.591911732
1.591911733 - 2.449448571
2.449448572 - 3.653991354
3.653991355 - 5.345957522
5.345957523 - 7.722585027
7.722585028 - 11.06092501
11.06092502 - 15.75013852
15.75013853 - 22.33686232
22.33686233 - 31.58893204


Response Density
with
Hot and Cool Crime Spots
of all Violent Crime Against Persons
N
0 0.125 0.25 0.5 Miles
Legend
MorvantHotSpot11-29-10
MorvantCoolSpot11-29-10
MorStreclipped
IDW Response Frequency
0.123878165 - 0.981415003
0.981415003 - 1.591911732
1.591911733 - 2.449448571
2.449448572 - 3.653991354
3.653991355 - 5.345957522
5.345957523 - 7.722585027
7.722585028 - 11.06092501
11.06092502 - 15.75013852
15.75013853 - 22.33686232
22.33686233 - 31.58893204

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CURRICULUM VITAE

Julie A. Hibdon was born on May 1, 1979 in Effingham, Illinois. Julie received her Bachelor of Arts Degree with double majors in Administration of Justice and Political Science from Southern Illinois University at Carbondale in 2001 and her Master of Arts Degree in Administration of Justice from Southern Illinois University, Carbondale in 2004. Upon completion of her M.A. Julie worked as a probation officer with the Marion County Court Services Department in Salem, Illinois. In 2005 she accepted admittance into the Doctor of Philosophy Program in the Department of Criminology, Law and Society and George Mason University. During her academic studies, Julie has served as a graduate research assistant to the Trinidad and Tobago Police Service Project (2005-2008) and a graduate research assistant (2008-2010), and later research associate (2010-present) for the Center of Evidence-Based Crime Policy housed within the Department of Criminology, Law and Society at George Mason University. Through these positions, she has worked and collaborated on many research projects including the Trinidad and Tobago Police Service Project (2005-2008), funded by the Trinidad and Tobago Ministry of National Security; License Plate Recognition Technologies for Law Enforcement project (2009-2010), funded by SPAWAR and NIJ; a comprehensive strategy evaluation of Transportation Security Administration security policy (2010-present), funded by the Department of Homeland Security; and most recently a grant evaluating the impact of technology on police organizations and practices, funded by the NIJ (2010-present). Julie's research interests include crime and place, crime and small-scale places, and the influence of environments on behaviors, particularly of criminal justice agents. Julie was a 2009-2010 PhD award recipient of the College of Humanities and Social Sciences Dean's Challenge Award. During her time as a student, she was an active member of the Criminology, Law and Society Student Association (CLSSA), serving as a founding member and the association's President in 2009-2010. Julie has accepted a post-doctorate research position with the Center for Evidence-Based Crime Policy at George Mason University that will begin upon completion of her doctoral degree.