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Childhood Obesity and Crime

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by

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Abstract

Childhood obesity is a significant health problem potentially influenced crime. This study employed secondary analysis of cross-sectional data using Geographic Information Systems for spatial comparison and logistic regression for statistical analysis. This was done to investigate the association between obesity, as measured by Body Mass Index of preschool children, and distance to the nearest instance of different categories of crime. Three covariates were included in the study: median family income, proportion of the population who self-identified as visible minorities, and straight-line distance from the child's postal code to the closest park or green space. Of the eight categories of crime studied, three categories of person crime (commercial robbery, street robbery and other violence) and one category of property crime (theft of vehicle) predicted childhood obesity. This research is unique, as it separated crime into eight categories for analysis, and measured the straight-line distance to crime, rather than using neighbourhood boundaries.

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"Aerodynamically, the bumble bee shouldn't be able to fly,

but the bumble bee doesn't know it so it goes on flying anyway."

Mary Kay Ash

Chapter 1: Introduction

1.1 The Obesity Epidemic

In Canada between 2009 and 2011, 31.5% of youth aged 5 to 17 were overweight or obese, based on their body mass index (BMI) (Active Healthy Kids Canada, 2012). BMI is calculated by dividing a child's weight in kilograms by their height in metres squared (Centers for Disease Control and Prevention, 2011). To determine if a child is obese the child's BMI is plotted by the child's age on a gender-specific, standardized growth chart (Centers for Disease Control and Prevention, 2011). See Appendix A for definitions. The rate of childhood obesity in Canada has increased 2.5 times in the last 30 years (Hodgson, 2011) and in the developed world childhood obesity is now the most common health issue affecting children (Rabbitt & Coyne, 2012). Childhood obesity is of concern to the nursing profession as it has health implications for the child that last well into adulthood (Akhtar-Danesh, Dehghan, Morrison, & Fonseka, 2011). These long-term health consequences include high blood pressure (Peters, Whincup, Cook, Law, & Li, 2012), type II diabetes, hyperlipidemia, adult obesity (Crawford, Story, Wang, Ritchie, & Sabry, 2001), gastroesophageal reflux disease (GERD) (Quitadamo et al., 2012), and asthma (Kornides, Kitsantas, Yang, & Villarruel, 2011). In addition to health issues, obesity has been linked to social issues. Children who are obese have lower rates of self-esteem (Kornides et al., 2011). Four- and five- year-old boys who are obese exhibit more behavioural and mental health problems across multiple scales as reported by both parents and teachers (Sawyer et al., 2006). Childhood obesity has also been linked to negative stereotyping and bullying (Rabbitt & Coyne, 2012). This growing body of literature suggests that childhood obesity is increasing, with associated increases in physical and mental health risks.

1.2 The Built Environment and Childhood Obesity

Historically, the role of diet and physical activity in childhood obesity have been a major research focus (Safron, Cislak, Gaspar, & Luszczynska, 2011). However, there is increasing evidence that no one individual level factor contributes exclusively to obesity (Sandy, Tchernis, Wilson, Liu, & Zhou, 2013). Health professionals and others have been encouraging physical activity for over 40 years (as seen through national ParticipACTION campaigns) and still only 7% of Canadian children are meeting national physical activity guidelines (Active Healthy Kids Canada, 2012). Although Canada's food guide recommends 5 to 10 servings of fruits and vegetables per day, one Canadian study showed less than half of youth surveyed reported eating fruits and vegetables more than once a day (Janssen, Katzmarzyk, Boyce, King, & Pickett, 2004). This raises questions as to the efficacy of current approaches to addressing childhood obesity. Recently, the role of children's environments, especially the built environment, has become a greater focus in childhood obesity research (Cecil-Karb & Grogan-Kaylor, 2009). While the built environment is often thought of as only an environment's physical infrastructure, the built environment is actually the "physical infrastructure (e.g., buildings, roads, and lighting) and outdoor spaces (e.g., parks and urban design) of a place, as well as the policies that shape them" (Miranda, Edwards, Anthopolos, Dolinsky, & Kemper, 2012, p. 750). Neighbourhood crime, which is shaped by both physical infrastructure and social policies (Miranda et al., 2012), can be regarded as one aspect of the built environment that has been identified as a potential concern for childhood obesity (Cecil-Karb & Grogan-Kaylor, 2009). High neighbourhood crime levels may contribute to rising levels of childhood obesity by limiting children's outdoor play and physical activity (Kalish, Banco, Burke, & Lapidus, 2010; Kimbro, Brooks-Gunn, & McLanahan, 2011), which can increase the amount of time they spend inside (Kimbro et al., 2011). It is also known that as parents perceive an increased risk of their child witnessing or being a victim of violence, they are less likely to allow outdoor play by their child (Kalish et al., 2010). Increased indoor play time is related to an increase in the amount of time children spend watching television and on the computer (Burdette & Whitaker, 2005), which is in turn related to increased obesity (Safron et al., 2011). Higher neighbourhood crime rates are also associated with higher neighbourhood unemployment rates, which are often used as measures for neighbourhood socioeconomic status (Lange et al., 2011). Lower parental education levels (Sakai, 2013), another measure for socioeconomic status, are associated with higher rates of childhood obesity. Thus, previous research has shown a relationship between high rates of neighbourhood crime and lower neighbourhood socioeconomic status (Lovasi, Hutson, Guerra, & Neckerman, 2009), which suggests a possible association between childhood obesity and crime. Currently however, evidence of the association between childhood obesity and crime is inconclusive.

1.3 Theoretical Framework

In order to better focus this research study, the crime and obesity variables are visualized within a systems theoretical model. In the discussion of childhood obesity, how children interact with their family, peers, school, and their environment, and the policies that influence all of these factors, are important to investigate, yet can be difficult to integrate with information relating to crime. One model that allows these factors to be discussed and better situated within the child's wider environment is Bronfenbrenner's bioecological model (Bronfenbrenner, 2004).

Bronfenbrenner's (2004) model provides a way to understand a child's development within a complex system of relationships and multiple levels of interactions with their environment

(Bronfenbrenner, 1994). Essentially, the model describes five interrelated and interrelating ecological systems. Children's lives are played out within these systems. The five systems are as follows:

1. Microsystem: The microsystem is the innermost layer of Bronfenbrenner's (2004) model. This represents how the child is situated within their own family and how their family interacts and supports the child. Diet and genetic factors also play a role in obesity (Magnusson, Sjoberg, Kjellgren, & Lissner, 2011), and there is a strong correlation between high parental BMIs and children who are obese (Washington, Reifsnider, Bishop, Ethington, & Ruffin, 2010). Children of parents who are obese also have a higher preference for fatty foods, a lower preference for vegetables, and a stronger affinity for sedentary activities, indicating a familial role in childhood obesity (Washington et al., 2010).
2. Mesosystem: The mesosystem includes interactions between various aspects of the microsystem (Bronfenbrenner, 2004). The child's wider environment such as their peers and their school environment influence child obesity as children spend a large part of their day with their peers and within a school environment. Schools can promote healthy eating through various policies and school nutrition programs play a key role in children's diets (Foltz et al., 2012). This is also true of school physical education policies and programs (Foltz et al., 2012).
3. Exosystem: The exosystem involves areas that affect children yet in which the child does not interact, mainly the areas in which their parents interact (Bronfenbrenner, 1986). For example, financial difficulties within the family, parental hardship, and so forth may affect a child, but do not involve the child directly. This is one area where crime may

affect children as crimes such a theft of vehicle can cause financial and organizational difficulties for parents. In the discussion of childhood obesity, the exosystem highlights parental influences, such as parents choosing fast food as they struggle to manage busy work and social schedules.

4. Macrosystem: The macrosystem is the outermost layer of Bronfenbrenner's (2004) model. This system includes social or cultural ideologies and beliefs that affect an individual's environment. The macrosystem refers to the overlaying policies that influence a child's life, as well as cultural influences. Therefore, this level is where most of the interactions between the built environment, crime and the child will be evident. Neighbourhood social processes such as social cohesion have recently been recognized for the role they play in childhood obesity (Kimbro et al., 2011), as well as the multitude of influences of the built environment on childhood obesity (Miranda et al., 2012).
5. Chronosystem: The chronosystem describes changes over time, such as maturation and family history (Bronfenbrenner, 1994). This level is highlighted by the family history of obesity, or parental obesity, as important indicators of the child's future risk of obesity (Washington et al., 2010).

The strength of using this model is that various levels of relationships are situated within this model. While this study examines the association between childhood obesity and crime, which places this study predominately in the *macrosystem* level of Bronfenbrenner's ecological model, the interactions across all levels are important in the discussion of childhood obesity. A wide variety of factors have been found to influence childhood obesity, from food choices (Janssen et al., 2004), to physical activity (Active Healthy Kids Canada, 2012), to the built environment (Cecil-Karb & Grogan-Kaylor, 2009). Crime also influences people both directly and indirectly

(Gupta et al., 2010). Therefore a model that facilitates an understanding of these various factors and interaction, which Bronfenbrenner's model provides through the use of a systems approach, was needed to better understand this study.

1.4 Research Aim

The aim of this study was to investigate the association between the BMI of preschool children and actual neighbourhood crime, after controlling for socioeconomic factors. Previous studies have shown that lack of perceived safety, or high levels of perceived crime, are associated with increased childhood obesity rates (Bacha et al., 2010; Burdette & Whitaker, 2005; Cecil-Karb & Grogan-Kaylor, 2009; Lorenc et al., 2012). However, perceptions of safety are quite different than actual safety and may not accurately reflect actual safety, and the association between perceived and actual crime is not well understood (Lorenc et al., 2012). Thus, this research focuses on *actual*, not perceived crime.

Chapter 2: Review of the Literature

The review of the literature will be presented in two sections. First, key concepts related to crime, including an exploration of the difference between perceived safety and actual crime will be presented, including a discussion of altruistic fear, social capital, incivility, and the media. Though the current study looks specifically at crime, not the perception of safety, this part of the literature provides background information to help understand why and how fear, whether from actual crime or perceived safety, can influence behaviour. This exploration will be followed by a narrative review of the literature related specifically to the association between childhood obesity and crime. The chapter will conclude with the purpose of this research and the specific research question.

2.1 Exploration of Key Concepts

Perceptions of Safety and Actual Crime

There is a lack of research about how perceived safety relates to actual crime rates. Lorenc et al. (2012), one of the few studies that looked at this disconnect, found no relationship between perceived safety and crime rates. Additionally, territoriality, such as security bars and "beware of dog" signs, were not associated with childhood weight status, whereas actual safety, based on crime data, was (Miranda et al., 2012). In a survey of adolescents and obesity Carroll-Scott et al. (2013) measured the perception of safety and actual crime. They found that while increased property crime was associated with higher BMI scores, the subjective measure of perceptions of safety had no association with BMI (Carroll-Scott et al., 2013). These studies suggest confusion between perceived safety and actual safety, and add weight to the notion that perceived safety should not be used as a proxy for, or indication of, an association with actual safety. There is a growing body of literature on the association between perceived safety, either of the parent or child, and childhood obesity, while there are few studies regarding a possible association between childhood obesity and actual crime (Lovasi et al., 2013). For clarity, perceived safety is a general term regarding neighbourhood factors more wide reaching than crime, including traffic safety (Durand, Dunton, Spruijt-Metz, & Pentz, 2012). Perceived crime is an emotional response to the possibility of crime (Lorenc et al., 2012) and fear of crime is how worried people are about specifically becoming a victim of crime (Lorenc et al., 2012). Both perceived crime and fear of crime are also encompassed in perception of safety. Crime is related to perceived safety and fear of crime, and certainly plays into how these perceptions are formed (Durand et al., 2012; Hale, 1996), but crime is an actuality whereas perception of safety, perceived crime, and fear of crime are personal constructs (Warr & Ellision, 2000).

Fear of Crime, Perceptions of Safety, and How They Are Formed

Fear of crime depends on a person's perception of becoming a victim and on how serious the consequences of victimization are likely to be (Hale, 1996). Having been a victim of any crime can increase the fear of residential break and enter, and other violence, though usually not the fear of street robbery, assault, or property crimes (Hale, 1996). Hale (1996) found a strong relationship between fear of crime and hearing about crimes from friends or neighbours. Hale suggested this occurred as acknowledging the similarities between the victim and the individual reinforce the individual's sense of vulnerability (Hale, 1996). Therefore actual crime can be seen to impact both perceived safety and fear of crime, and it certainly influences how these perceptions are formed. However, perceived safety and fear of crime may not accurately reflect crime rates (Lorenc et al., 2012).

Overall men are more likely to be the victims of crime, yet women and the elderly tend to feel less safe than men do (Gardner, 1990; Hale, 1996). In a study about how Canadians felt about crime and their personal safety, 93% of Canadians aged 15 years and older were satisfied with their personal safety from crime (Brennan, 2011). Most Canadians felt safe in their homes and neighbourhoods: 83% said they were not at all worried when home alone in the evening, and 90% said they felt safe when walking alone in their neighbourhood at night (Brennan, 2011). However, 62% of Canadians believed that the amount of crime in their neighbourhood was the same as 5 years earlier, while 26% felt that crime had increased; and only 6% perceived that crime had decreased (Brennan, 2011). In Calgary, 57% of people said crime in their city was lower than in other Canadian cities; 29% said crime was about the same; and only 10% said it was higher (Brennan, 2011).

Altruistic Fear for the Safety of Others

Altruistic fear, or the fear for the safety of others, is an added dimension to the discussion of perception of safety. Parents are more likely to fear for the safety of their children than for themselves (Busselle, 2003; Warr & Ellision, 2000). As perception of safety is influenced by many individual and cultural factors, simply providing information on crime is ineffective in decreasing or resolving fear of crime (Jackson, 2004; Van Bruncshot, Laurendeau, & Keown, 2009). Altruistic fear may be more easily influenced by the media than personal fear of crime (Tulloch, 2004). This is especially relevant in the context of parental fear of crime, which is more difficult to align with actual crime (Warr & Ellision, 2000). Increased observation of crime by parents was found to have also increased estimates of the likelihood of crime by their adolescent children, which suggests that fear of crime can be transmitted to children through precautionary warnings (Busselle, 2003). In the discussion of childhood obesity and crime, altruistic fear is especially important as both children's fear, and their parent's altruistic fears, are envisioned to play a role in this possible association.

Social Capital

Social capital, or the sense of community spirit and involvement, has been hypothesized to mitigate crime both directly and indirectly (Takagi, Ikeda, & Kawachi, 2012). Direct mitigation of crime can occur by increasing the social supports and coping mechanisms of neighbourhood members. Indirect mitigation of crime can occur by providing a collective 'eyes on the street' mentality, which has been shown to decrease neighbourhood crime (Takagi et al., 2012). Neighbourhoods with high social capital report much lower fear of crime (Takagi et al., 2012), even when higher crime rates actually exist (Hale, 1996). The relationship between fear and behaviour is sometimes portrayed as a downward spiral in which fear causes people to change their behaviour and this response in turn heightens their fear (Hale, 1996; Takagi et al., 2012). This downward spiral can be mitigated by high levels of social capital. Fear of crime may also lead to increased crime levels as behavioural changes that keep people home and away from certain spaces and resources, such as public transit, will reduce the level of general surveillance, which can in turn lead to increases in crime (Takagi et al., 2012).

Incivility

Incivility, the 'signs of crime' seen in neighbourhoods such as graffiti, vandalism or garbage on the street, increase the fear of crime (Keown, 2008b; Takagi et al., 2012), and are related to social capital, as higher levels of social capital are correlated with lower levels of incivility (Takagi et al., 2012). Signs of incivility indicate that the area may not be well cared for and this can lead to increase illegal activities, such as drug dealing and public drinking, further reinforcing feelings that the neighbourhood is unsafe (Keown, 2008b), even if the crime rate is relatively low (Hale, 1996). Personal experience, media reports and the comments of friends and family also affect people's perceptions of incivility (Keown, 2008b). In Calgary, 2004 data indicated that 13% of people felt there was some type of physical incivility in their neighbourhood, which was less than the national average of 16% (Keown, 2008b). Areas with high housing density or near the city centre reported more incivility, with a sharp contrast between urban and suburban neighbourhoods (Keown, 2008b). Overwhelmingly, research has found that fear of crime is complex and that factors such as reduced incivility and increased social cohesion may decrease crime rates more than traditional crime prevention measures (Jackson, 2004).

The Media

The media plays a role in fear of crime with their focus on serious or sensational crime, and with the media being the main source of vicarious information for many people (Hale, 1996). Hearing in the local media about victims who are comparable or those who live in similar neighbourhoods can increase people's fear of crime, although reports of crime in other cities or countries did not seem to have as large an impact (Hale, 1996). Data from 2003 show that nearly all Canadians access news media at least several times a week, most commonly through television, although those living in rural areas or who speak French have greater difficulty with access (Keown, 2008a). News media have been shown to focus extensively on violent crime

(Busselle, 2003), although this is the least prevalent type of crime. Television reporting and portrayals of violence on television increase the fear of crime, estimates of crime's prevalence and crime related precautionary behaviours (Busselle, 2003). While the connection between media reported crime and fear of crime would seem to be fairly straightforward, people internalize media reports differently, again adding complexity to determining how each person's perception of safety is formed.

Distance to Crime and Arbitrary Administrative Boundaries

How far away a crime has to be before it no longer influences a person's perception of safety is exceedingly complicated. Most often, aspects of the built environment, including crime, are studied at the neighbourhood level, although the description of 'neighbourhood' varies, with the most frequent description being the use of arbitrary administrative boundaries (Kruger, 2008; Takagi et al., 2012; Wisnieski, Bologeorges, Johnson, & Henry, 2013). There are many questions about whether administrative boundaries are actually capturing how people define their 'neighbourhood' and how they move and interact with their local environment. Kruger (2008) used the physical condition of residential and commercial buildings to model fear of neighbourhood crime and found they were directly related. The relationship between the condition of residential buildings and perceptions of crime were highest between 0.2 and 0.35 miles (0.32 to 0.56 km), while the condition of commercial structures influenced perceptions the most at a distance of 1.05 miles (1.69 km) (Kruger, 2008). The Bayesian model of pedestrian walking distances comes from a study of the average distance that people will walk to shopping, work, and transit (Seneviratne, 1985), which was found to be a distance of 0.25 miles (0.4 km). While this does not seem to make this the appropriate optimal distance to use for examining perceptions of crime, work by Kruger (2008) showed that the relationship between the condition of residential buildings and perceptions of crime were highest between 0.2 and 0.35 miles (0.32 to 0.56 km). This may indicate that the Bayesian model's 0.25 miles (0.4 km) measure is an appropriate distance on which to base the perception of crime for residential built environment factors.

Resident-framed definitions of 'neighbourhood' have been proposed, although these have been said to be subjective and labour- and time-intensive (Weiss, Ompad, Galea, & Vlahov, 2007; Wisnieski et al., 2013). Wisnieski et al. (2013) used qualitative reporting of local crime, incivilities and disorder to determine how close crimes that people heard about or witnessed were from their residences. The average distance to witnessed crimes was 0.44 miles (0.71 km) and was 0.70 miles (1.13 km) for incidents that respondents had heard about (Wisnieski et al., 2013). Additionally, Wisnieski et al. (2013) asked respondents if reported crimes occurred within one block of their home, and of these crimes the average reporting radius was 0.3 miles (0.48 km), indicating that 0.3 miles (0.48 km) is the distance residents perceive as being 'one block' from their home. Fights and beatings were more likely than other crimes to be perceived by respondents as within 'one block' of their home (Wisnieski et al., 2013). Therefore using the Bayesian model of pedestrian walking distances, which proposes using a distance of 0.25 miles (0.4 km) from the residence of the respondent may be a good model to investigate perception of residential crimes (Kruger, 2008; Wisnieski et al., 2013). However to understand perceptions of commercial crime, researchers need to consider a distance greater than 0.25 miles (0.4 km) (Kruger, 2008).

In summary, the concepts of perceptions of safety, fear of crime and actual crime, altruistic fear, incivility, social capital, media, and distance to crime influence perceptions of crime and safety. While lack of perceived safety is correlated with increased rates of childhood obesity (Bacha et al., 2010; Cecil-Karb & Grogan-Kaylor, 2009; Lumeng, Appugliese, Cabral, Bradley, & Zuckerman, 2006), perceptions of safety are quite different from actual crime and may not accurately reflect actual safety, and the association between perceived and actual crime is not well understood (Lorenc et al., 2012). Thus, this research focuses on *actual*, not perceived, crime.

2.2 Narrative Review

To better understand the association between childhood obesity and crime, a narrative literature review was undertaken. A narrative review was selected because an understanding of the association between childhood obesity and crime is just emerging (Popay et al., 2006). A narrative approach provided a broader base of knowledge about the topic from which other studies can build. The guiding question for the review was: "Does crime influence childhood obesity, and if so, how does this occur?"

Literature Search

Searches were conducted of the electronic databases PubMed, CINAHL plus, Medline via Ovid, GEOBASE, PsycINFO, Canadian Health Research Collection, and ProQuest Dissertations and Theses in September 2014. The search terms used were obesity terms (obesity, overweight, body mass index, BMI and body weight) combined by the Boolean Operator *or*, and crime terms (crime, neighbourhood crime, and neighbourhood safety) combined by the Boolean Operator *or*. Obesity terms and crime terms were combined with the modifier *and*.

Inclusion and Exclusion Criteria

Inclusion and exclusion criteria were determined before searches were initiated. See Table 1. Studies were excluded if they used parental perceptions of neighbourhood safety, rather than actual crime data. Articles regarding person-specific crimes, such as childhood sexual abuse, childhood neglect or witnessing domestic abuse or violence were also excluded, because these types of crimes have a different effect on children than do more general crimes (Gupta et al., 2010). Finally, studies where it was impossible to determine the specific effect of crime on childhood obesity levels specifically were also excluded. This included two systematic reviews that looked at the effects of many neighbourhood characteristics on weight and physical activity in children, but did not discuss the specific effect of crime on childhood obesity levels.

Table 1

Review Inclusion and Exclusion Criteria

	Population	Exposure	Study Designs	Outcome	Additionally
Included	- Children (aged 0-18 years)	- Crime, as measured by actual crime statistics	- Primary studies	- BMI	- English language -Peer reviewed - Published after 2000
Excluded	- Adults, anyone over the age of 18 years	- Parental perceptions, or general perceptions, of crime - Person-specific crimes (such as childhood sexual abuse, or witnessing domestic abuse or violence)	- Commentaries	- Other measures of weight - Other factors related to crime such as physical activity	- Gray literature

Study Selection

Search results were scanned for titles that potentially met inclusion criteria, after which abstracts of all potentially relevant titles were reviewed. If potentially relevant articles appeared to meet inclusion criteria, or did not meet exclusion criteria, the full text was reviewed. To determine final articles for inclusion in the review, differences of opinion regarding article inclusion were resolved by discussion and consensus of the supervisory committee.

Data Extraction and Quality Assessment

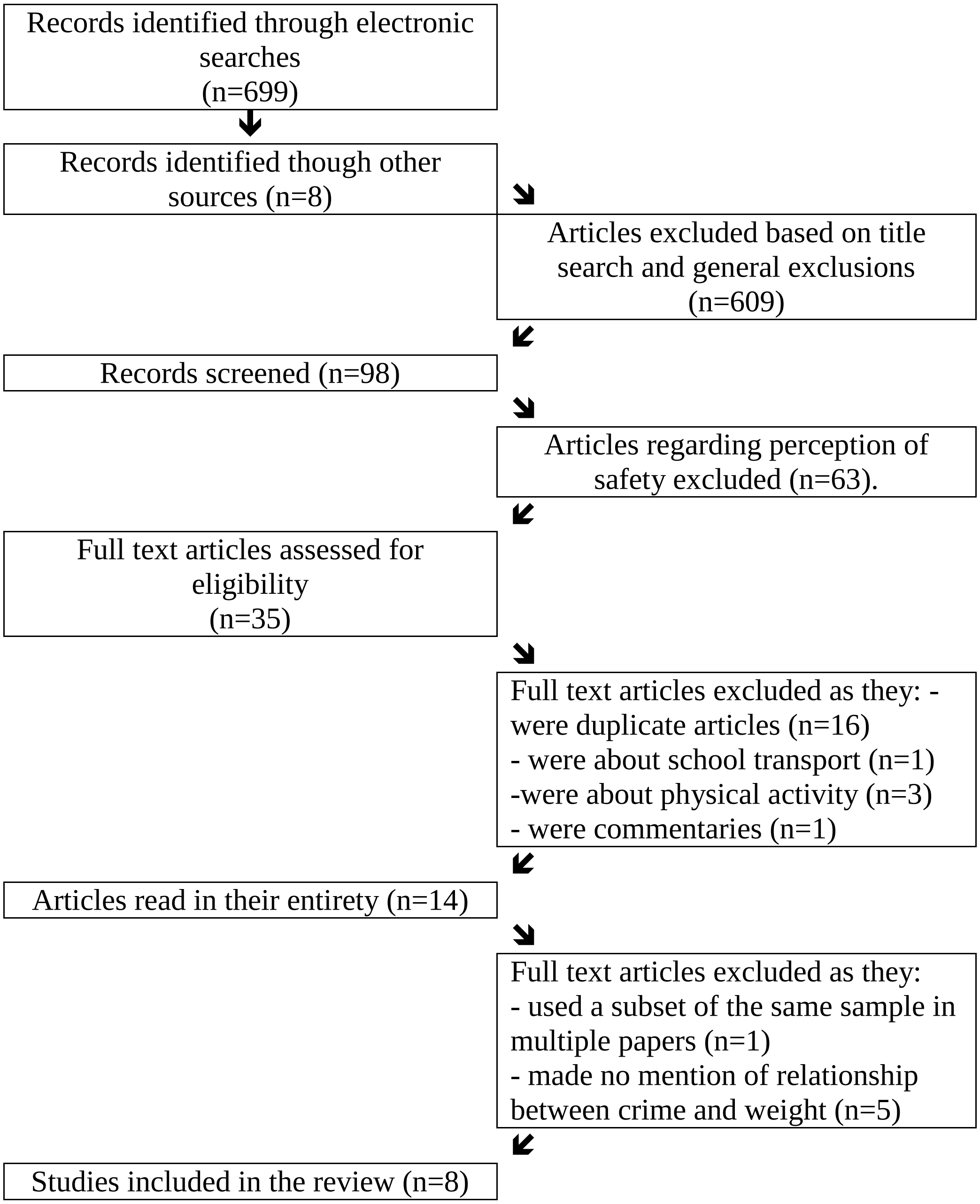
An investigator created tool was used to extract the data. The information collected from each study included: (a) location, (b) research method (c) sample size, (d) independent and dependent variables, (e) age range of participants, (f) study results, and (g) limitations discussed in the study. The Mixed Methods Appraisal Tool (MMAT) was used to assess study quality. The MMAT was developed to enable comparison of studies with different methodologies included in a mixed study review (Pace et al., 2012). The MMAT captures clarity of the study reporting of study objective, selection bias, appropriateness of measurements, group difference, and percent of outcome data available. Study quality is measured in 25% increments from 0% to 100%; higher scores indicate higher quality studies. The MMAT did not place studies in the hierarchy of evidence (Pace et al., 2012), however all included studies were cross-sectional descriptive designs, so determining study hierarchy was unnecessary. A tool that allowed comparison of methodologies was unnecessary as all the included studies were cross-sectional, however this was not known when the tool was selected and this tool was felt to best capture the relative merits of the studies. Although the quality of studies was variable, all selected studies were included because they added valuable information to the review.

Search Results

There were 699 articles initially identified through database searches with an additional eight articles identified through hand searches of reference lists, for a total of 707 articles. Of these, 609 were excluded based on title review, leaving 98 abstracts for review. Of these 63 were found to be about perceptions of safety, rather than crime, which was the focus of this study, and were therefore excluded. Thus, 35 full articles were selected for initial review. During initial review, 16 were found to be duplicates, and five additional articles were excluded, as they did not meet inclusion criteria. In total, 14 articles were read in their entirety and had their reference lists hand searched. A few of the studies that seemed to meet all inclusion criteria used various methods to model the general effect of many neighbourhood factors on children's obesity levels. However, on careful examination it was impossible to untangle the association between childhood obesity and crime; therefore, these five additional studies were excluded. One study, Lovasi et al. (2011), met the inclusion criteria but was excluded as it analyzed a subset of the dataset of the Lovasi et al. (2013) study. Therefore the review includes eight articles.

Figure 1

PRISMA Flow Diagram of Search



Narrative Review Results

Of the eight studies included, six were conducted in the United States (Burdette & Whitaker, 2004; Carroll-Scott et al., 2013; Grafova, 2008; Lange et al., 2011; Lovasi et al., 2013;

Miranda et al., 2012; Sandy et al., 2013) with the remainder conducted in Japan (Sakai, 2013) and Germany (Lange et al., 2011). Population samples were used for most of the United States studies (Carroll-Scott et al., 2013; Grafova, 2008; Miranda et al., 2012; Sandy et al., 2013), the German study (Lange et al., 2011) and the Japanese study (Sakai, 2013). The ages of the children studied ranged considerably. Burdette and Whitaker (2004), and Lovasi et al. (2013) studied preschool children. Sakai (2013) included 5-to 17-year-olds, but analysis focused exclusively on the 17-year-olds in the sample. Carroll-Scott et al. (2013) studied 10- to 12-year-olds, and Lange et al. (2011) studied 13- to 15-year-olds. The remainder (Grafova, 2008; Miranda et al., 2012; Sandy et al., 2013) studied a range of ages from preschool to adolescent children. The most recent studies came from Miranda et al. (2012) who used 2008 to 2009 data, and Sakai (2013) who used 2008 data. Carroll-Scott et al. (2013) used 2009 data for individual level variables, but 2000 census data for neighbourhood variables. The majority of the studies used GIS mapping to describe the association between childhood obesity and crime, except Lange et al. (2011) who used multilevel modeling, Sakai (2013) who used linear regression, and Grafova (2008) who used logistic regression.

Critical appraisal scores for the eight included studies ranged from 0 to 100%. See Table 3 for scores and rationale for scores. The majority of the studies were highly ranked with two ranked at 100% (Grafova, 2008; Lange et al., 2011) and five at 75% (Burdette & Whitaker, 2004; Carroll-Scott et al., 2013; Lovasi et al., 2013; Miranda et al., 2012; Sakai, 2013). The article by Sandy et al. (2013) received the lowest critical appraisal score of 50%.

Table 2

Article Descriptions

Study	*Location*	*Research Method and Design*	*Sample*	*Variables*	*Age Range*	*Results*	*Limitations*
Burdette, H. & Whitaker, R., 2004 (Burdette & Whitaker, 2004)	Cincinnati, Ohio, USA	Quantitative, cross-sectional, GSI Mapping	*N* = 7,020	Dependent: BMI. Independent: proximity of residences to playgrounds and fast food restaurants and the rate of violent crimes and 911 calls.	3- to 5-year-old	Proximity to playgrounds and level of neighbourhood crime were not significantly associated with childhood overweight, after controlling for poverty ratio, child race, and child gender. Observed but non-significant association between weight and playground proximity.	Data from low-income children only. Studied crime in neighbourhood, not by distance to the child's residence. Used violent crime and 911 call rates as proxy for crime, the later not reflecting actual crime.
Carroll-Scott, A., et. al., 2013 (Carroll-Scott et al., 2013)	New Haven CT, USA	Quantitative, cross-sectional, GIS Mapping	*N* = 1,048	Dependent: BMI, frequency of healthy and unhealthy eating, frequency of physical activity, and amount of screen time. Independent: built environment, socioeconomic environment, and the social environment (including safety).	10- to 12-year-olds, mean age 10.9 years	Higher BMI was associated with living in neighbourhoods with more property crime. Violent crime had no association with BMI.	Studied crime in the children's neighbourhood (as measured by census tract), not by distance to the child's residence.

Grafova, I., 2008 (Grafova, 2008)	USA national data	Quantitative, cross-sectional	*N* = 2,907	Dependent: BMI. Independent: five characteristics reflecting neighbourhood urban sprawl and walkability and three socio-economic environment measures.	5- to 18-year-olds	No association was seen between pedestrian safety, crime, and weight status of children. However, increased rates of childhood obesity in neighbourhoods where physical disorder was observed.	Some environment features were measured at a county of residence level and others at a census tract level. Studied crime in the children’s neighbourhood not by distance to child's residence.
Lange, D., et. al., 2011 (Lange et al., 2011)	Kiel, Germany	Quantitative, cross-sectional	*N* = 3,440	Dependent: BMI. Independent: media time, dietary behaviour, unemployment rate, traffic density, population density, crime rate, and number of fields and parks.	13- to 15-year-olds	Crime rate had no effect on adolescent BMI. High crime was positively associated with high media time and neighbourhood unemployment rate, used as a proxy for neighbourhood SES.	Studied crime by neighbourhood, not by distance to the child's residence. No indication of how much time adolescents spend outside of their neighbourhoods, perhaps in neighbourhoods with lower crime rates and more green space.
Lovasi, G., et. al., 2013 (Lovasi et al., 2013)	New York, NY, USA	Quantitative, cross-sectional, GIS Mapping	*N* = 11,562	Dependent: BMI and physical activity. Independent: walkability, green space and safety (homicide rate and pedestrian-auto injury).	3- to 5-year-olds	A difference in homicide rates from the 25th to the 75th percentile was associated with a 22% higher prevalence of obesity.	Data from low-income children, only. Used homicide rate as a proxy for crime.

Miranda, M. et. al., 2012 (Miranda et al., 2012)	Durham, USA	Quantitative, cross-sectional, GIS Mapping	*N* = 1,785	Dependent: BMI. Independent: Property disorder, nuisances, violent and total crime, housing damage, territoriality, vacancy, and tenure.	2- to 18-year-olds	After adjustment for race, age, sex, and insurance status, property disorder, nuisances, violent crime, and total crime were significantly associated with increased BMI. Territoriality (such as security bars and "beware of dog" signs), was not associated with BMI.	Assumed that children sought care at their neighbourhood health clinic. Studied crime by neighbourhood, not by distance to the child's residence.
Sakai, R., 2013 (Sakai, 2013)	Japan	Quantitative, cross-sectional	*N* = 695,980	Dependent: obesity. Independent: food stores and restaurants, total length of roads, population density, number of cars, traffic accidents, criminal offenses and death by accidents.	5-to 17-year-olds	No association seen between obesity levels and crime or death by accidents.	Independent variable data came from different years. Studied crime by neighbourhood, not by distance to the child's residence.
Sandy, R. et. al., 2012 (Sandy et al., 2013)	Indianapolis, USA	Quantitative, cross-sectional, GIS Mapping	*N* = 37,000	Dependent: BMI and obesity status. Independent: crime and walking trails.	3- to 16-year-olds, mean age 8 years	Walking trails had a beneficial effect on children's BMI in low crime areas, but not in high crime areas.	Crime data not available in the same format for each county studied.

Note. GIS = geographic information system; BMI = body mass index; SES = socioeconomic status.

Table 3

Critical Appraisal Scores and Rationale for Scores (organized by score)

Article	Critical Appraisal Rating	Rationale for Critical Appraisal Rating
Grafova, I., 2008 (Grafova, 2008)	100%	-
Lange, D., et. al., 2011 (Lange et al., 2011)	100%	-
Burdette, H. & Whitaker, R. C., 2004 (Burdette & Whitaker, 2004)	75%	Recruitment was not done in a way that minimized confounders.
Carroll-Scott, A., et. al., 2013 (Carroll-Scott et al., 2013)	75%	Outcome data based on 68% of the sample.
Lovasi, G., 2013 (Lovasi et al., 2013)	75%	Recruitment was not done in a way that minimized confounders.
Miranda, M. et. al., 2012 (Miranda et al., 2012)	75%	Outcome data based on 74% of the sample.
Sakai, R., 201 3(Sakai, 2013)	75%	Did not provide the numbers on which the analysis was based just the beginning sample size. Full analysis was completed with only part of the sample.
Sandy, R. et. al., 2013 (Sandy et al., 2013)	50%	Recruitment was not done in a way that minimized confounders. No information provided on final and starting sample sizes, nor response rates.

Narrative Review Discussion

A discussion of the results of this review will be presented in the next section. The section starts with a discussion of the need for multiple measures of crime, then discusses the associations between childhood obesity and socioeconomic status, proximity to playgrounds and green space, and finally ends with a summary of the narrative review and why the current study was needed based on the narrative review.

Overall, the studies in the review failed to show a conclusive association between childhood obesity and crime, though an association is certainly possible. Lange et al. (2011) found that neighbourhood crime had no effect on BMI levels. Sakai (2013) showed there was no association between obesity levels and crime or death by accidents. Grafova (2008) found no association between children's weights and pedestrian safety or neighbourhood crime. Burdette and Whitaker (2004) found that neighbourhood crime was not associated with children's weights. Of those studies that did find some positive associations, Sandy et al. (2013) found that walking trails had a beneficial effect on children's weights in low crime areas, but not in high crime areas (Sandy et al., 2013). Miranda et al. (2012) found that property disorder, nuisances, violent crime, and total crime were significantly associated with increased BMI levels, after adjustment for race, age, sex, and insurance status. Carroll-Scott et al. (2013) found that living in neighbourhoods with more property crime was associated with a higher BMI, though this was not the case for neighbourhoods with higher rates of violent crimes. Lovasi et al. (2013) found an increase in homicide rates from the 25th to the 75th percentile was associated with a 22% higher prevalence of obesity. In summary, four studies showed a positive association between childhood obesity and certain types of neighbourhood crime (Carroll-Scott et al., 2013; Lovasi et al., 2013; Miranda et al., 2012; Sandy et al., 2013), and four (Burdette & Whitaker, 2004; Grafova, 2008; Lange et al., 2011; Sakai, 2013) showed no association.

Categories of Crimes

Different crimes affect people differently (Gupta et al., 2010), so identifying which types of crime were included in the dataset of the studies in the review could help to illustrate associations specific to particular categories of crime. There is limited research regarding crime's influence on health conditions, however previous research which looked at the relationship between crime and the prevalence of childhood asthma found that both drug abuse violation and violent crime were associated with childhood asthma prevalence, but only violent crime remained significantly associated with childhood asthma prevalence after adjusting for ethnicity (Gupta et al., 2010). Also the density of violent crime around adolescents' homes was significantly related to girls' outdoor physical activity, but not to boys' physical activity (Gomez, Johnson, Selva, & Sallis, 2004). It is known from research on how the perception of safety is formed that fear of crime seems to depend on a person's perception of becoming a victim and on how serious the consequences of victimization are likely to be; having been a victim can increase fear of residential break and enter, and other violence, though not fear of street robbery, assault, or property crime (Hale, 1996). This indicates that the effect of crime is not universally the same, but varies with category of crime, therefore studies need to recognize and acknowledge the different effects of various categories of crimes.

Interestingly, three studies used a single measure of violent crime such as homicide rate (Burdette & Whitaker, 2004; Lovasi et al., 2013; Sandy et al., 2013) while three studies used a measure of total crime, which included all criminal offences, but integrated these offences into one measure without looking separately at different types of crimes (Lange et al., 2011; Miranda et al., 2012; Sakai, 2013). Only two studies, Grafova (2008) and Carroll-Scott et al. (2013), separated crime into a measure of violent crime and property crime. This did not seem to influence whether an association was found however, as the three articles that demonstrated a positive association between childhood obesity levels and certain types of neighbourhood crime used the homicide rate (Lovasi et al., 2013), a measure of total crime (Miranda et al., 2012), and a measure that separated crime into violent crime and property crime (Carroll-Scott et al., 2013). Research from within the review and from other areas, such as the perception of safety, indicated that separating crime into various categories may offer the greatest potential for understanding the underlying association between childhood obesity and crime.

Low Income or Socioeconomic Status

One study found that children living with a lower socioeconomic status were 11% more likely to be overweight and 9% more likely to be obese (Oliver & Hayes, 2005), results which have been replicated by other researchers (Magnusson et al., 2011). An association between lower socioeconomic status and increased neighbourhood crime has also been established (Theall, Sterk, & Elifson, 2009). Higher neighbourhood crime rates have also been found to be associated with higher neighbourhood unemployment rates, which were used as a proxy measure for neighbourhood socioeconomic status (Lange et al., 2011). Lower parental education levels (Sakai, 2013), another proxy measure for socioeconomic status, were associated with higher rates of childhood obesity. This aligns with previous research that showed an association between high rates of neighbourhood crime and a lower neighbourhood socioeconomic status (Lovasi et al., 2009). Also, higher neighbourhood crime rates were associated with higher rates of screen time (Lange et al., 2011). Children were also likely to watch more television if their parents perceived their neighbourhoods as unsafe (Burdette & Whitaker, 2005). Other factors associated with increased children's weights were neighbourhoods where physical disorder was observed (Grafova, 2008). Burdette and Whitaker (2004) and Sandy et al. (2013) used data exclusively from low-income children as a way to control for socioeconomic status. While this is not detrimental to the studies by Burdette and Whitaker (2004) and Sandy et al. (2013), it does limit the generalizability of these results to all children. Generalizability is desirable, although in studies with complex associations, such as between childhood obesity and crime, it may be challenging to achieve a balance between controlling for confounders and generalizability. As socioeconomic status has been found to influence childhood obesity, and has been found to be associated with crime rates, it should be controlled for in analyses looking for an association between childhood obesity and crime.

Proximity to Playground and Green Space

A study by Potestio et al. (2009) showed that childhood obesity was not associated with access to parks and green spaces. However, other studies have shown that greater availability of parks and green space (Wolch et al., 2011) and closer proximity of playgrounds (Burdette & Whitaker, 2004) decreased obesity rates in children. Studies have also shown that the simple addition of play equipment to children's school play spaces increased moderate to vigorous physical activity (Hannon & Brown, 2008). Showing that while study results regarding accessibility are mixed, playgrounds do overall increase fitness. A further study by Fan and Jin (2013) found that when playgrounds were provided in neighbourhoods that were perceived as unsafe by parents, there was a greater reduction in obesity rates then when playgrounds were provided in neighbourhoods perceived as safe. This was speculated to be a result of children in neighbourhoods perceived as safe having more activities available to them, such as recreation centers (Fan & Jin, 2013). Overall, it is unclear whether access to parks and green space decreases rates of childhood obesity, however this relationship is likely complex.

Problems with Area Measurements

Most often aspects of the built environment, including crime, are studied at the neighbourhood level, although how 'neighbourhood' is defined varies and is most often defined by arbitrary administrative boundaries (Kruger, 2008; Takagi et al., 2012; Wisnieski et al., 2013). This raises questions about whether administrative boundaries are actually capturing how people define their 'neighbourhood' and how they move and interact with their local environment. This question has been debated in recent literature, with administrative boundaries appearing not to be the best representation of built environment effects (Kruger, 2008; Takagi et al., 2012; Wisnieski et al., 2013). Using the Bayesian model of pedestrian walking distances, which proposes using a distance of 0.25 miles (0.4 km) from the residence of the respondent, has been suggested for the study of built environment factors such as crime (Kruger, 2008; Seneviratne, 1985; Wisnieski et al., 2013). A more fluid definition of neighbourhood framed by residents' perceptions of 'neighbourhood' has also been proposed (Wisnieski et al., 2013), though such perceptions have been said to be subjective and labour- and time-intensive (Weiss et al., 2007; Wisnieski et al., 2013). The US Census Tract and ZIP Code level measurement areas are administratively defined areas and have been found to often contain several distinct neighbourhoods, thus masking individual neighbourhood effects (Kruger, 2008). Of the studies in this review, five of the eight studies used larger areas defined by administrative boundaries, such as Census Tracts, Tax Parcels, and Districts (Carroll-Scott et al., 2013; Grafova, 2008; Lange et al., 2011; Miranda et al., 2012; Sakai, 2013). Burdette and Whitaker (2004) used 'neighbourhoods' although there was no indication of how the boundaries of these areas were calculated, so they may have been administratively defined as well. Sandy et al. (2013), and Lovasi et al. (2013) both used a smaller 'buffer' zone around each child's home address, which is more in keeping with both the Bayesian model of pedestrian walking distances and a more fluid definition of neighbourhood framed by residents (Kruger, 2008). Whether administrative boundaries or smaller buffer zones were used did not seem to greatly influence whether an association between childhood obesity and crime was found. The articles demonstrating a positive association between childhood obesity levels and certain categories of neighbourhood crime (Carroll-Scott et al., 2013; Lovasi et al., 2013; Miranda et al., 2012) used Tax Parcels (Miranda et al., 2012), Census Tracts (Carroll-Scott et al., 2013) and buffer zones (Lovasi et al., 2013). However, Miranda et al. (2012) used tax parcels, which appear to be quite small, and Carroll-Scott et al. (2013) noted that in the area where their study was conducted, Census Tracts (the measurement area used) had been found to closely resemble resident derived neighbourhoods. The other issue with administratively derived boundaries is that they measure crime only in the child's neighbourhood as opposed to measuring it by distance to the child's residence. Therefore, crimes that may be close, but not actually in the child's neighbourhood, were not captured. While it is somewhat unclear, the use of administratively derived boundaries may have obscured some associations between childhood obesity and crime in some of the included studies.

Summary of the Narrative Review

The results of this review point to the possibility that there is an association between childhood obesity levels and crime, though this is still quite unclear. Childhood obesity itself is associated with multiple factors (Grafova, 2008), so in some ways it is hardly surprising that an association between childhood obesity and crime is complex. Such a complex association would explain why some studies found a relationship and others did not. Specifically, the study by Sandy et al. (2013) is worth mentioning as it showed that walking trails have a beneficial effect on children's weights in low crime areas, but not in high crime areas. This was the only study to report the different effects of neighbourhood factors on children's weights in low versus high crime neighbourhoods. The study authors hypothesized that this effect was due to trails becoming places for crimes to be perpetrated in higher crime neighbourhoods (Sandy et al., 2013), which helps to illustrate the complexity of the relationship between childhood obesity levels and crime.

Need for Current Study

Of the eight studies in the review, four studies showed a positive association between childhood obesity and certain types of neighbourhood crime (Carroll-Scott et al., 2013; Lovasi et al., 2013; Miranda et al., 2012; Sandy et al., 2013), and four (Burdette & Whitaker, 2004; Grafova, 2008; Lange et al., 2011; Sakai, 2013) showed no association. Some of the methodological weaknesses of the studies, such as (a) using data from low-income children, only, (b) using administratively derived boundaries, (c) using older data, and (d) narrowly defining crime, may have obscured underlying associations. Therefore, further studies need to look at the association between childhood obesity and crime, and these studies need to include:

- a population-based sample of children, controlling for socioeconomic status;
- distance to crime data that is calculated using a buffer around the child's home, not data that is based on administratively derived boundaries;
- crimes separated into different categories, not crime data that uses one measure of crime generally or simply uses violent crime data.

These gaps are addressed in the current study by examining the association between childhood obesity and neighbourhood crime, as measured through crimes perpetrated. The results of the current study can be generalized to a wider population of children, use both BMI and crime data from the year 2011, focus on proximity to crime by using the actual distance from each child's home to the location of the nearest crime, and divide crimes into four categories of person crimes and four categories of property crimes.

2.3 Research Question

The research question for this study was: "What is the association between individual level Body Mass Index (BMI) of 4 to 6 year old children, in Calgary, Canada, and neighbourhood level crime, after controlling for neighbourhood level income, neighbourhood level parental education, neighbourhood level visible minorities, and proximity to parks and green space?"

Chapter 3: Methods

3.1 Context

This study was conducted with data collected in Calgary, a large city in Western Canada with a 2011 population of 1,214,839 (Statistics Canada, 2012a). Calgary consists of a total of 218 individual neighbourhoods. In 2011, 18.3% of the population was under the age of 15 years, with 62.1% of families having children (Statistics Canada, 2012a). The majority (70.9%) spoke English, 1.5% spoke French and 25.3% spoke other languages (Statistics Canada, 2012a). Of people aged 25 and older, 67.2% had completed some form of postsecondary education, with 38.3% reporting a university certificate or degree, 19.7% reporting a college diploma and 9.1% reporting a trades certificate (Statistics Canada, 2012a).

3.2 Study Design

This study employed secondary analysis of cross-sectional data using Geographic Information Systems (GIS) as a tool for spatial analysis. The dependent variable was rate of childhood obesity, as measured by the Center for Disease Control Weight Percentile Cut Offs (Centers for Disease Control and Prevention, 2011). This metric categorized children's weights into underweight, normal weight, overweight, and obese. The independent variable was distance to the nearest instance of each category of crime (person crimes including commercial robbery, street robbery, assault and other violence; and property crimes including theft of vehicle, theft from vehicle, and commercial and residential break and enter) (see the section on Crime Data for a full explanation of the crime categories). The covariates were (a) median family income in dollars, (b) proportion of the neighbourhood with a university degree, (c) proportion of the population who were a visible minority and (d) distance to the closest park or green space, in meters.

3.3 Study Data

Data for this study included: (a) 2011 BMI data for children seen in Public Health clinics in Alberta Health Services, Calgary Zone with their residential postal codes, (b) 2011 crime data for the City of Calgary with postal codes indicating where the crime occurred, (c) 2006 Canadian Census data with neighbourhood level income, parental education, and visible minorities, and (d) the geographical location of Calgary parks and trails. Given that crime information was limited to the City of Calgary boundaries, only BMI data from this area were included. Data for 2011 were selected because both crime and BMI data were available for that year.

BMI Data

The BMI data are held as part of the immunization data set (referred to as PHANTIM) collected by Alberta Health Services, Calgary Zone. BMI and the postal code were collected for children at their pre-school immunization clinic visit. The information on children's BMIs was collected by Public Health Nurses who were trained in how to obtain accurate measurements and followed strict protocols that included who to measure, how to correctly measure, and when to calibrate equipment. Children were between the ages of 4 and 7 years old when the BMI measurements were taken; measurements were not taken if (a) children were late for the appointment or uncooperative, (b) had a disability that made height or weight measurements difficult, (c) had implements such as a cast, or (d) the parents refused. For this study, included variables were: a six digit postal code, sex, height, weight, BMI, BMI percentile, age on immunization date, and immunization date. Records with improbable BMI numbers (above 60 or below 10) were removed.

Crime Data

The crime data were publicly available as part of the Calgary Police Service Crime Mapping database (available at http://crimemap.calgarypolice.ca/). However, this website provides the number of crimes per neighbourhood, and postal codes were required to calculate actual distance to crimes. Therefore, Calgary Police Service gave access to the postal code associated with each crime. Eight categories of crime, which made up two larger types, were used: (a) person crimes (commercial robbery, street robbery, assault and other violence), and (b) property crime (commercial break and enter, residential break and enter, theft of vehicle and theft from vehicle) (Calgary Police Services, 2013). These categories were devised by the Calgary Police Service, as different crimes affect neighbourhoods differently (Sakip, Johari, & Salleh, 2012). Assault includes crimes such as assault, aggravated assault, unlawfully causing bodily harm, discharging a firearm with intent, using a firearm and criminal negligence causing bodily harm (Canadian Center for Justice Statistics, 2013). Other violence includes crimes such as murder, manslaughter, attempted murder, kidnapping forcible confinement, and uttering threats (Canadian Center for Justice Statistics, 2013).

Domestic crime (domestic assault and domestic violence) was excluded because it is a more personal type of crime (S. Jervis, Calgary Police Service, personal communication, January 16, 2014). Disorder was excluded because very few of these crimes had a postal code or completed address associated with them, so most instances could not be mapped (S. Jervis, personal communication, January 16, 2014). Each crime data point was categorized based on the most serious violation per incident as determined by Calgary Police Service. Cases that were unfounded after investigation were removed by Calgary Police Service.

The Calgary Police Service records management software contained all public and police generated calls with a variety of information about the crime and the location at which the crime occurred, so the dataset was cleaned by Calgary Police Service prior to being received. Calgary Police Service removed all information other than the date, location and type of crime, and ensured that a postal code was provided. All police-generated and unfounded reports were removed. Finally, the crime data were sorted by type of crime and domestic and disorder crimes were removed. This final dataset was then received through email as an excel document for use in this study.

Census Data

Family income, parental education, and visible minorities within neighbourhoods were obtained from the Canadian Census using the neighbourhood profiles. The data for the 2006 Census was used because the 2011 Canadian Census neighbourhood profiles were not available at the time of the study. Historically, there has been little variability in this information for each neighbourhood across multiple censuses, based on a visual inspection of trends and evidence (Heisz, 2005), including anecdotal evidence. Also in the 2011 census, there was an increased non-response rate for the long-form census, as compared to the 2006 census, due to the long-form census no longer being mandatory (Statistics Canada, 2013). This non-response rate potentially limits the representativeness of the sample, and the generalizability of the results. Thus, it was decided that the 2006 Canadian Census data was more appropriate for this study.

Data from the 2011 City of Calgary Census was also used. This city census provided the number of people, and the specific number of preschool children, in each City of Calgary neighbourhood. This information was access through the University of Calgary, Spatial and Numeric Data Services. The City of Calgary, Census Community Boundary layer file was also used to determine the neighbourhood boundaries.

Parks Data

Information on parks and trails was obtained from the City of Calgary. These data were available through the University of Calgary, Spatial and Numeric Data Services, as a layer file, which was needed for use within the ESRI ArcGIS [computer software] (www.esri.ca) that was used for the GIS portion of this study. This information identified the parks maintained by City of Calgary, as well as trails and pathways.

3.4 Creating the BMI and Crime Datasets

The BMI and crime data were mapped using postal codes to create the final BMI and crime datasets. All mapping of the datasets was done using ESRI ArcGIS [computer software] (www.esri.ca). To begin cleaning and mapping the BMI data, BMI records that had no postal code, or an obviously incorrect postal code, were removed from the sample. The remaining records were mapped using ArcGIS. The National Postal Code Conversion File (PCCF), which contains a list of the latitude and longitude of all postal codes in Canada (Statistics Canada, 2013) was obtained from the University of Calgary, Spatial and Numeric Data Services. The PCCF was then used to create an Address Locator, which is a geographic reference of each postal code made using their latitude and longitude. The BMI file was then opened in ArcGIS and the Address Locator was used to map the BMI data points by assigning each BMI data point the latitude and longitude associated with its postal code as a reference point (similar to a linking variable). Some BMI data records were unable to be mapped as their postal code did not match a reference postal code from the PCCF, and were therefore excluded. The publicly available City of Calgary, Census Community Boundary layer file was downloaded into ArcGIS and superimposed on the same map as the BMI data points. This allowed only the BMI data points that fell within the City of Calgary boundaries to be selected to create the final BMI dataset consisting of 10,069 records. The Join by Location function was used to join the neighbourhood data from the City of Calgary, Census Community Boundary layer file with each record in the dataset. This linked each record in the dataset with neighbourhood information from the 2011 City of Calgary Census. Please see Figure 2 – Sample Inclusion Flow Diagram for BMI Data in the results section for a visual representation of this process.

The City of Calgary Census Community Boundaries did delineate arbitrarily defined communities. However, based on the urban growth pattern these communities were formed as a result of social, historical and geographic criteria (Gauvin et al., 2007). Therefore previous research has shown that these communities are relatively homogeneous (Gauvin et al., 2007).

This process was then repeated with the crime data. All crime data records including a postal code were loaded into ArcGIS and the Address Locator created from the PCCF was used to map the crimes. Crimes that had a postal code that did not match a reference postal code in the PCCF were excluded. The map of all the crimes was then compared to the City of Calgary, Census Community Boundary layer file and crimes outside the city boundaries were excluded. This created the final crime dataset consisting of 19,275 crimes. The final crime dataset was joined to the City of Calgary, Census Community Boundary layer file information tying each crime to the neighbourhood in which it was committed and to information about the 2011 City of Calgary Census population in each neighbourhood.

After the final BMI and crime datasets were created in ArcGIS, they were exported as separate Excel files. These two separate datasets were used to create maps and to calculate the distances between the children and crime events (see section 3.6 Spatial Analysis to Create Distance to Crime); however, the datasets were never merged. Using Excel software, the frequency of each type of crime was calculated from the total number of each type of crime and divided by the 2011 City of Calgary census population. The BMI dataset was imported into the Statistical Package for the Social Sciences (SPSS) (Version 21) [computer software] from the Excel file.

Once a final dataset with mappable BMI points was created (descriptive analysis dataset), it was compared with the deleted BMI data. This data was from the BMI data initially received from Alberta Health Services but which had been eliminated from the final dataset due to non-Calgary or unmappable postal codes. The final dataset and the deleted dataset were compared based on the age of the children using an unpaired t-test. Chi Squared tests were used to look for differences in the proportion of the samples who were female and who were obese.

3.5 BMI and Crime Density, Proportion Mapping

Two maps were created. The BMI map shows the proportion of obese children, aged 4 to 7 years, in each City of Calgary neighbourhood. The crime map shows the crime density in the City of Calgary. The two maps were created using the *Join Spatial* tool in ArcGIS to locate each BMI or crime point with their neighbourhood in the City of Calgary, Census Community Boundary layer file.

For the BMI proportion map, only the records of children who were obese were selected from the full BMI dataset. The selected records were then joined with their neighbourhood in the City of Calgary, Census Community Boundary layer file, using the *Join Spatial* tool. This allowed the number of obese children in each neighbourhood to be summed. The sum of the children who were obese was then divided by the total number of children from this study in each neighbourhood to create the proportion of obese children in each neighbourhood. This proportion is represented by a color gradient on a map of Calgary. The total number of children from some neighbourhoods was small, which created misleading proportion numbers. For example, if one child in a neighbourhood was obese and there was a total of only three children this meant that one third of the children were obese, which was misleading. Therefore, neighbourhoods with a sample total of less than five children were excluded from the BMI proportion map.

For the crime density map, the *Join Spatial* tool in ArcGIS was used to locate each crime within the City of Calgary, Census Community Boundary layer file, thus allowing the number of crimes per neighbourhood to be summed. The total number of crimes in each neighbourhood was then divided by the total population, based on the 2011 City of Calgary Census. This crime density was represented by a color gradient on a map of Calgary. All neighbourhoods with available data were represented on the crime density map, regardless of the number or type of crimes. This was decided as there were only a small number of communities which had lower numbers of crimes, due to the larger number of crimes relative to the number of obesity children.

3.6 Spatial Analysis to Create Distance to Crime

In order to determine the distance from each child's postal code to the location of the crime, the *Near* tool from the Proximity Toolbox was used. This tool calculated the straight-line distance, in meters, from each feature in one group to the nearest feature in another group. In this study, the *Near* tool was used to calculate the straight-line distance from each child's postal code to the nearest location of crime. The straight-line, rather than the driving distance, was used. First, the distance to any type of crime was calculated to create a total crime variable. Then, the distance to each specific category of crime (i.e., commercial robbery, street robbery, assault, other violence, vehicle theft, and break and enter) was calculated. This spatial analysis produced the information for the distance to crime independent variable.

In terms of the geographic variable, other studies generally used arbitrarily defined administrative boundaries (Kruger, 2008; Takagi et al., 2012; Wisnieski et al., 2013). However administrative boundaries do not appear to best represent how people define their 'neighbourhood' and how they move and interact with their 'neighbourhood' (Kruger, 2008). Using the Bayesian model of pedestrian walking distances (Kruger, 2008; Seneviratne, 1985; Wisnieski et al., 2013), or a more fluid definition of neighbourhood framed by residents perceptions of 'neighbourhood' (Wisnieski et al., 2013), have been proposed to better study neighbourhood effects. However, these classification systems are labour and time consuming to determine (Weiss et al., 2007; Wisnieski et al., 2013). In this study the distance to crime was studied more directly using straight-line distances, rather than road network distances. While this was mainly done to simplify GIS calculations, using straight-line distances, versus road network distance, has been found to be equivalent to driving distance for 90% of the population, when considering non-emergency travel in urban areas (Boscoe, Henry, & Zdeb, 2012). Most importantly, by using a direct measure of distance to crime, through the use of straight-line distances, the effects of crimes that occurred close to a child's residence, but outside their neighbourhood, or other arbitrarily defined administrative boundary, were captured in the analysis.

3.7 Descriptive Analysis

The datasets were analysed using the Statistical Package for the Social Sciences (SPSS) (Version 21) [computer software] with $p < 0.05$ considered significant. The *frequencies* function was used to produce descriptive information about the BMI and crime variables, as well as the covariates. The *frequencies* function was also used to provide descriptive information about the distance to crime variable.

3.8 Defining the Dependent Variable for Logistic Regression Analysis

There are four possible BMI percentile categories (underweight, normal weight, overweight, and obese) (Centers for Disease Control and Prevention, 2011). However, the normal weight and obese categories were chosen specifically for the logistic regression analysis. The possibility of combining the overweight and obese categories was discussed at length. However, levels of physical fitness, ethnicity, frame size, and biological maturation are not taken into account in BMI calculations (Colman, Hayward, Moffatt, & Coupland, 2010), thus, some normal weight children may be misclassified as overweight (see the limitations section for a full discussion). This means that some children who have the overall health profile of a normal weight child may actually be classified as overweight. Based on this possibility of misclassification, the fact that being obese is more concerning to health than is being overweight, and that the research question specifically related to obese children, BMI was categorized as normal weight or obese. Thus, 1,244 overweight and 447 underweight children were excluded (16.8% of the sample) for a final sample of 8,378 children for the logistic regression analysis.

3.9 Testing of Logistic Regression Assumptions

Before modeling could begin, the assumptions of logistic regression were examined. These assumptions were: (a) the dependent variable must be dichotomous, (b) the dependent variable must be mutually exclusive and exhaustive, (c) larger samples are needed as maximum likelihood coefficients are large sample estimates, and (d) a linear relationship must exist between the continuous predictors and the log odds of the dependent variable (Lund Research, 2013).

The obese BMI percentile group was the dependent variable, with the normal weight group being the reference group. This variable is therefore dichotomous, and the assumption was met (Lund Research, 2013). The exclusive assumption was met as children could be in only one weight category; therefore, the categories were exclusive. The categories were exhaustive as the possible outcome options were either normal weight or obese for the included categories. In terms of sample size, since there were 7,521 in the normal weight category and 857 in the obese BMI category, the assumption of a larger sample size was satisfied (Katz, 2011). Finally, the linearity of the continuous predictors versus the log odds of the dependent variable was tested. The variables versus the log odds of the dependent variable were graphed and the resulting lines were visualized to ensure they were linear (see Appendix B for the results of these tests). All independent variables (distance to crime and covariates) were linear with the log odds of BMI (the dependent variable); therefore, they were used as continuous variables. The data met the assumptions for logistic regression analysis, so this analysis was performed.

3.10 Identifying the Independent Variables for Logistic Regression Analysis

Crime

Some of the studies identified in the literature review used a measure of total crime (Lange et al., 2011; Miranda et al., 2012; Sakai, 2013); however, different categories of crime affect people differently (Gupta et al., 2010). Separating crime into categories provides greater depth and ability to more fully understand whether different crimes also affect children's obesity differently. A measure of total crime, namely the distance to the closest instance of any type of crime, was used in the descriptive analysis; however, only the eight specific categories of crime variables were used in the logistic regression analysis. The crime variables that were used for the logistic regression analysis were from the previously described spatial analysis, so each crime variable was the distance from the child's postal code to the nearest instance of that type of crime. The eight categories of crime were organized into two types: (a) person crimes (commercial robbery, street robbery, assault and other violence), and (b) property crime (theft of vehicle, theft from vehicle, commercial break and enter, and residential break and enter).

While looking separately at different types of crimes made a lot of sense theoretically, the reality was far more complicated. Originally it was thought that the eight different categories of crime used in this study could be integrated into the same logistic regression model. However, when testing of logistic regression assumptions began, it was discovered that the crime terms were collinear, which meant they could not be integrated into the same model. This collinearity is not entirely surprising as neighbourhoods that have high levels of one type of crime are likely to have high levels of other types of crime. So rather than moving to using just one measure of crime, eight different logistic regression models were created, one for each different category of crime. This did ultimately address the issue of collinearity among the crime categories, and allowed for the examination of the effects of each different category of crime; however, it resulted in a far more complicated logistic regression analyses.

Covariates

The covariates used in the logistic regression analyses were theoretically derived from the literature and were (a) the median family income in dollars for the child's neighbourhood, (b) the proportion of the child's neighbourhood with a university degree, (c) the visible minority proportion in the child's neighbourhood and (d) the straight-line distance from the child's postal code to the closest park in meters. The first three covariates were from the neighbourhood profiles of the 2006 Canadian Census. The *Join Attribute* tool was used to join the 2006 Canadian Census data with the BMI data records based on the neighbourhood in which the child's residential postal code was located. Therefore, values were the same for every child living in the same neighbourhood. All covariates were used as continuous variables.

The distance to the closest park covariate was calculated using spatial analysis in the same way that distance to the crime was calculated. This was using the *Near* tool from the Proximity Toolbox to calculate the straight-line distance from each child's postal code to the closest park or green space, in meters.

3.11 Testing of Multicollinearity for the Logistic Regression Analysis

A zero-order correlation matrix was used to test for collinearity. This matrix was created in SPSS by using the *Correlate, Bivariate* tool to calculate the Pearson's correlation coefficient. The convention is that if a coefficient is greater than 0.8 it suggests that two independent variables explain more than half the variance being examined, and that one of the variables should be removed from final modeling (Katz, 2011). For this study, the median family income variable and the proportion of the neighbourhood with a university education variable were found to have a Pearson correlation coefficient of 0.78. It was decided that the median family income variable should be kept in the analysis, rather than the education variable, as a measure of income was used more commonly in the literature review studies (Burdette & Whitaker, 2004; Lovasi et al., 2013; Sakai, 2013), than was education. While the Pearson correlation coefficient was not greater than the 0.8 cut-off, based on the theoretical relationship between the two variables and previous studies, university education was excluded from the logistic regression analysis.

3.12 Testing of Interactions for the Logistic Regression Analysis

Based on previous research, there were possible theoretical interactions among the covariates median family income, proportion of the community who were a visible minority, and distance to parks (Drewnowski, Rehm, & Solet, 2007; Potestio et al., 2009). Therefore, these were tested using the interactions portion of the *Regression, Binary Logistic* tool. No interactions were found (see Appendix B). The specific crime categories used in this study have never previously been tested in studies of this type (see literature review for a full discussion); therefore, there was no theoretical basis to test interactions between the crime categories used in this study, or between the crime categories and covariates. In addition, interaction effects create challenges in the interpretation of the results.

3.13 Logistic Regression Analysis Modeling

After testing assumptions, and analyzing interactions and multicollinearity, there were eight models created. The models contained obese children as the dependent variable, with normal weight children as the reference, one of the eight crime categories (commercial robbery, street robbery, assault, other violence, residential break and enter, commercial break and enter, theft of vehicle and theft from vehicle) as the independent variable, and the three covariates (median family income, the visible minority proportion and the distance to the closest park in meters). The modeling was done using the *Regression, Binary Logistic* tool in SPSS with simultaneous entry of the independent variables.

Once the output was produced in SPSS a number of tests were examined. The omnibus test of model coefficients was checked to ensure it was statistically significant ($p < 0.05$), which allows rejection of the null hypothesis that all of the predictors effects are zero. The Hosmer-Lemeshow Goodness of Fit test was done; if this test is statistically significant ($p < 0.05$) then the model is significantly different from a perfect model and is therefore not a good fit, although this test can be problematic with larger samples sizes. The Wald statistic was checked to see whether the predictors in the model were statistically significant ($p < 0.05$). Results of these tests are discussed in the results section. Finally, the Odds Ratio showed by how much each predictor variable increased or decreased the odds of the dependent variable. The Odds Ratio, Wald statistic and 95% confidence intervals were calculated for all models.

3.14 Ethical Considerations

Permission to conduct this study was received from The Conjoint Health Research Ethics Board at the University of Calgary, study ID REB13-0621. In addition, a data agreement was signed with Alberta Health Services for the BMI dataset. Human subjects were not involved directly in the study; rather the BMI data were accessed retrospectively from the Alberta Health Services database. The BMI dataset did not include any identifying information thus protecting each child's confidentiality. Six-digit postal codes were used to situate both the BMI and crime data points to ensure greater precision of the data. The postal code locations were used for analytical purposes only, and were not mapped as individual points. The major ethical concern for this study was the use of data for purposes other than for which it was originally collected. Parents were not told that their children's data were going to be used for this specific study, and the data were administrative data, so no consent form was obtained. It was impractical and unreasonable to obtain consent for this study, as participants would have been very difficult to contact, and logistically contacting that many people would have been impractical. No consent was sought for the crime data, and no data agreement was requested by Calgary Police Services, as the data were collected as part of their mandate.

Chapter 4: Results

4.1 Descriptive Statistics

Characteristics of Children and BMI Weight Groups

The final BMI dataset consisted of 10,069 children who lived in Calgary and had postal codes that could be geocoded for 2011 (see Figure 2 *Sample Inclusion Flow Diagram for BMI Data*). There were no statistically significant differences found between the children whose postal code could not be geocoded (deleted dataset) and those who were included in the descriptive analysis (descriptive analysis dataset), see Table 4. Of the sample, 48.8% were female and 51.2% were male with an average age of 59.87 (*SD* = 6.67) months (minimum 54 - maximum 84 months) or approximately 5 years. See Table 5 for frequency and percent of children in each weight group. Canadian BMI percentages are provided for comparison. Canadian BMI percentages for 3 to 5-year-olds were 2.5% underweight, 65.5% were normal weight, 17.5% were overweight and 14.5% were obese (Statistics Canada, 2012b), also using CDC BMI percentile cut offs.

Figure 2

Sample Inclusion Flow Diagram for BMI Data

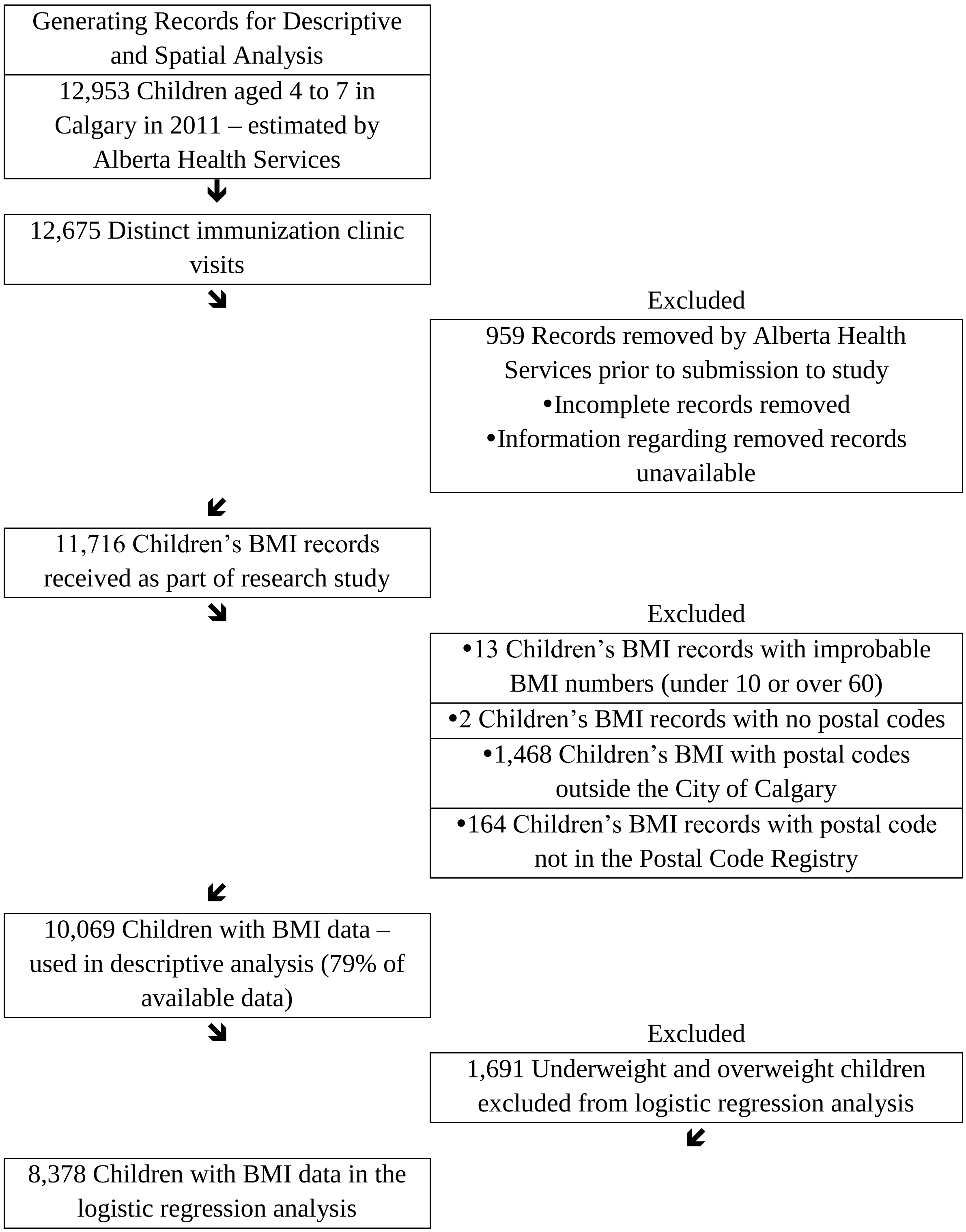


Table 4

Differences Between Dataset Used for Descriptive Analysis and Deleted BMI Data

	Descriptive Analysis Dataset (N = 10,069)	Deleted Dataset (N = 1,647)	Statically Significant Difference
Age (months)	59.87 (mean)	60.09 (mean)	No ($p = 0.228$)
Female (proportion of sample)	48.8%	49.9%	No ($p = 0.413$)
Obese (proportion of sample)	8.5%	8.3%	No ($p = 0.727$)

Table 5

Frequency and Percent of BMI Weight Category for Study and Canadian Children

Weight Category	Study	Canadian [a]
	Frequency (Percentage)	Percentage (Confidence Interval)
Underweight	447 (4.4)	2.5 (1.4, 4.5)
Normal Weight	7521 (74.7)	65.5 (60.3, 70.4)
Overweight	1244 (12.4)	17.5 (11.9, 24.9)
Obese	857 (8.5)	14.5 (9.7, 21.0)

Note. Sample size was 10,069 children. [a] Data from the Canadian Health Measures Survey, Cycle 2 (Statistics Canada, 2012b).

Crime Characteristics

Overall there were 19,275 crimes in the City of Calgary in the year 2011. Property crimes were more frequent than person crimes, with 14.25 property crimes per 1,000 people and 3.42 person crimes per 1,000 people. Of person crimes, non-domestic assault was the most frequent with 2,103 instances in 2011 or a frequency of 1.93 crimes per 1,000 people. The most frequent type of property crime, and crime generally, was theft from vehicle with 7,569 instances or a frequency of 6.94 crimes per 1,000 people. See Table 6.

Table 6

The Frequency of Categories of Crimes in the City of Calgary for 2011

Larger Crime Category	Crime Category	Frequency	Number per 1,000 people
Person Crimes	Commercial Robbery	261	0.24
	Street Robbery	313	0.29
	Assault (Non-domestic)	2,103	1.93
	Violence 'Other' (Non-domestic)	1,052	0.96
Property Crimes	Residential Break & Enter	3,164	2.90
	Commercial Break & Enter	1,923	1.76
	Theft of Vehicle	2,890	2.65
	Theft from Vehicle	7,569	6.94
Total		19,275	17.67

Note. Sample size 19,275 crimes. City of Calgary census population of 1,090,936 for 2011.

Characteristics of Covariates

See Table 7 for the characteristics of preschool children in terms of: income, university education, proportion visible minorities, and distance to parks. Children who were obese lived in neighbourhoods that (a) had a lower average family income, (b) had lower proportions of university education, (c) had higher proportions of visible minorities, and (d) were closer to parks, than children in any other weight category did.

Table 7

Income, University Education, Visible Minorities and Distance to Parks by BMI Weight Category

Covariate	Weight Category	Percent of Children	Mean (*SD*)	Maximum [a]
Median Family Income ($)	Underweight	4.4	83,028 (26,701)	213,901
	Normal Weight	74.7	86,704 (29,026)	293,665
	Overweight	12.4	82,454 (25,958)	213,900
	Obese	8.5	78,586 (24,463)	190,046
Percent of Neighbourhood with a University Degree (%)	Underweight	4.4	36 (16)	94
	Normal Weight	74.7	37 (16)	94
	Overweight	12.4	35 (15)	77
	Obese	8.5	32 (15)	94
Percent Visible Minority in a Neighbourhood (%)	Underweight	4.4	28 (19)	82
	Normal Weight	74.7	25 (17)	91
	Overweight	12.4	26 (18)	91
	Obese	8.5	30 (19)	82
Distance to the Closest Park (meters)	Underweight	4.4	141.18 (188.18)	1389.52
	Normal Weight	74.7	142.28 (180.59)	3497.83
	Overweight	12.4	140.64 (169.85)	1591.45
	Obese	8.5	137.66 (172.60)	1405.69

Note. BMI sample size of 10,069 children. [a] The minimum value for all categories was 0.

Distance from Children's Postal Code to Nearest Crime

In the next section, Tables 8, 9 and 10 show data results for the distance analysis, which is divided into person (Table 8), property (Table 9), and total crime (Table 10). The average distance between the child's postal code and the closest instance of each category of crime was calculated and is presented by weight category. This shows that, on average, children who were obese lived closer to all types of crimes than did children of normal weight. Also, children who were underweight lived closer to many types of crime than did children of normal weight, including commercial robberies, street robberies, assault, other violence, theft of vehicle, commercial break and enter. In terms of total crime, children who were obese on average lived only 39.51m from the closest instance of any type of crime while normal weight children lived an average of 49.97m. However, none of these calculations were adjusted to account for differences in family income, education level, or proportion who were a visible minority between children in different weight categories, all of which have been found to be associated with childhood obesity rates (Magnusson et al., 2011; Singh, Kogan, Van Dyck, & Siahpush, 2008).

Table 8

Mean Distance from Child's Postal Code to Nearest Person Crime by Weight Category

Crime Category	Weight Category	Percent of Children	Mean Distance (meters) (Standard Deviation)	Maximum Distance[a] (meters)
Commercial Robberies	Underweight	4.4	1131.36 (856.21)	4799.95
	Normal Weight	74.7	1196.54 (848.12)	5094.61
	Overweight	12.4	1141.98 (849.88)	5094.61
	Obese	8.5	1042.24 (773.10)	4118.77
Street Robbery	Underweight	4.4	1462.99 (1353.11)	6493.53
	Normal Weight	74.7	1605.30 (1398.48)	8394.41
	Overweight	12.4	1525.34 (1425.03)	6680.51
	Obese	8.5	1288.85 (1276.74)	6581.27
Assault (non-domestic)	Underweight	4.4	428.63 (376.58)	1885.71
	Normal Weight	74.7	451.07 (373.65)	3865.91
	Overweight	12.4	418.49 (361.18)	2396.65
	Obese	8.5	384.49 (352.08)	1994.64
Other Violence (Non-domestic)	Underweight	4.4	383.47 (319.82)	2338.74
	Normal Weight	74.7	438.27 (341.57)	3656.05
	Overweight	12.4	411.03 (344.43)	2505.53
	Obese	8.5	361.16 (298.69)	2321.31

Note. BMI sample size of 10,069 children. [a] The minimum distance for all categories was 0m.

Table 9

Mean Distance from Child's Postal Code to Nearest Property Crime by Weight Category

Crime Category	Weight Category	Percent of Children	Mean Distance (meters) (Standard Deviation)	Maximum Distance[a] (meters)
Residential Break and Enter	Underweight	4.4	169.71 (166.33)	890.00
	Normal Weight	74.7	168.87 (158.07)	1575.59
	Overweight	12.4	166.18 (151.98	1242.00
	Obese	8.5	148.88 (141.25	820.00
Commercial Break and Enter	Underweight	4.4	455.41 (315.83	1680.30
	Normal Weight	74.7	474.25 (321.73)	3991.49
	Overweight	12.4	459.63 (313.75)	1817.42
	Obese	8.5	444.03 (295.42)	1829.08
Theft of Vehicle	Underweight	4.4	254.74 (237.96)	1077.00
	Normal Weight	74.7	282.87 (252.60)	2020.81
	Overweight	12.4	263.10 (258.68)	2020.81
	Obese	8.5	229.34 (220.99)	1143.00
Theft from Vehicle	Underweight	4.4	103.73 (121.46)	869.85
	Normal Weight	74.7	101.85 (122.19)	3050.82
	Overweight	12.4	101.28 (113.29)	634.57
	Obese	8.5	93.78 (110.71)	635.00

Note. BMI sample size of 10,069 children. [a] The minimum distance for all categories was 0m.

Table 10

Mean Distance from Child's Postal Code to Nearest Total Crime Category by Weight Category

Weight Category	Percent of Children	Mean Distance (meters) (Standard Deviation)	Maximum Distance[a] (meters)
Underweight	4.4	50.19 (83.96)	749.45
Normal Weight	74.7	49.97 (78.07)	1162.82
Overweight	12.4	48.80 (74.81)	571.85
Obese	8.5	39.51 (66.70)	359.12

Note. BMI sample size of 10,069 children. [a] The minimum distance for all categories was 0m.

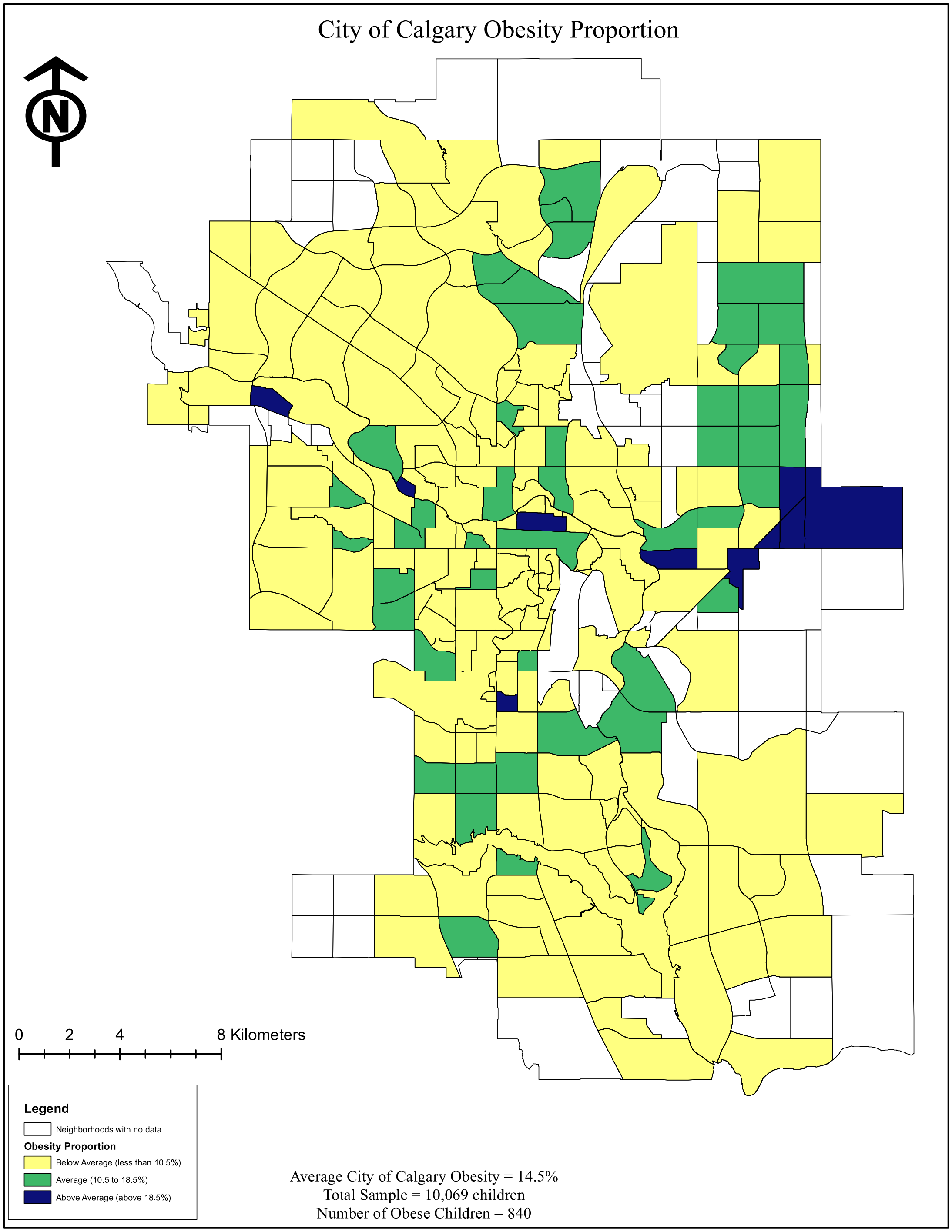
4.2 BMI Proportion and Crime Density Maps

BMI Proportion Map

A map of the number of children who were obese in each neighbourhood as a proportion of the total number of children in each neighbourhood from this sample was created to visualize the childhood obesity data. For the entire sample, 8.5% of the children were obese, however the average neighbourhood level obesity rate was 14.5%. In order to easily visualize the differences in communities, three categories were used: below the city average (under 10.5%), around the city average (10.5 to 18.5%), and above the city average (over 18.5%). Overall the majority of neighbourhoods were below the city average of 14.5% of children who were obese, though pockets of above average rates of obesity were seen in the northeast of the city.

Figure 3

Proportion of Obese Children in Each City of Calgary Neighbourhood

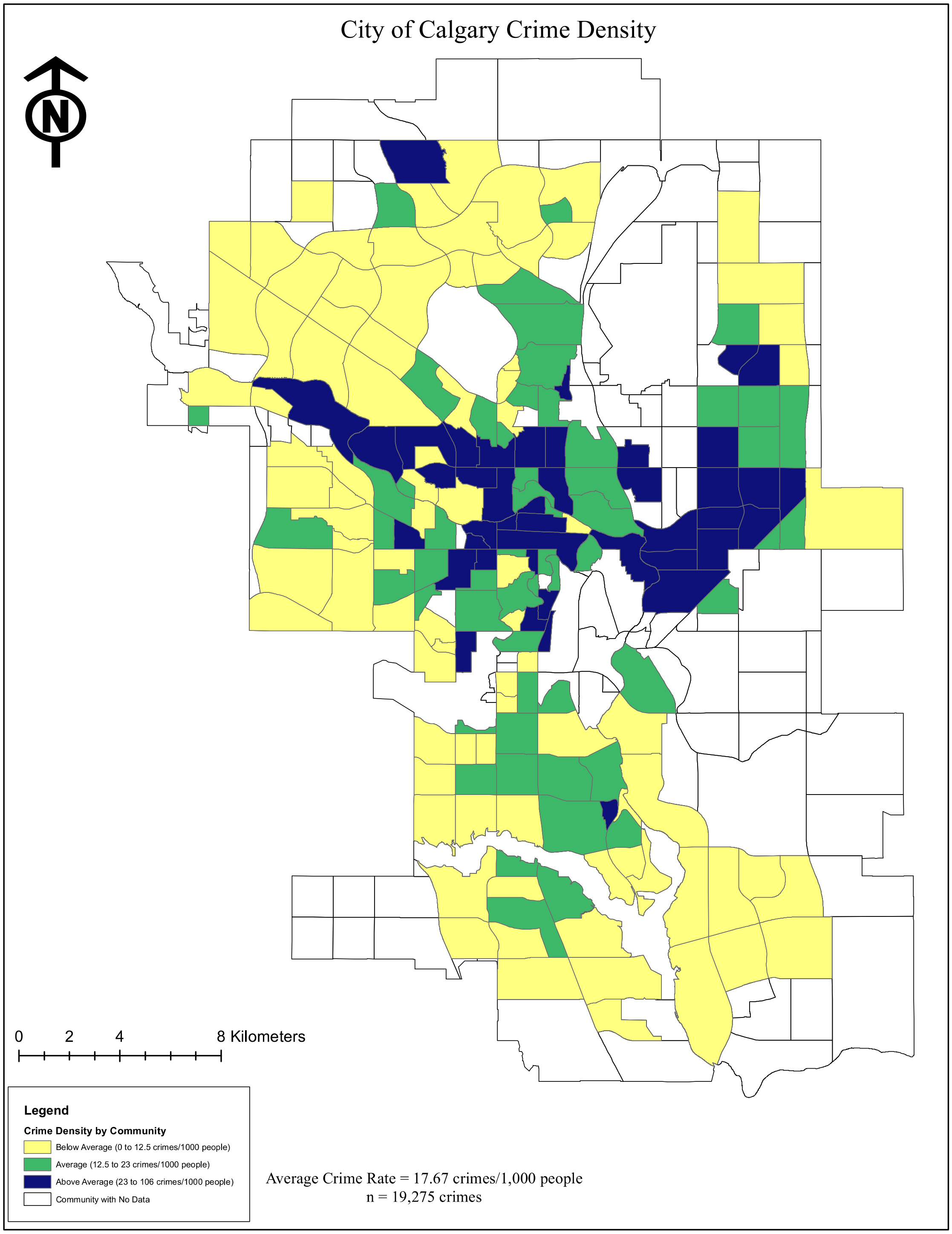


Crime Density Map

To visualize the crime density for the City of Calgary, a map of the total number of crimes per 1,000 people was created. The average crime rate for the city was 17.67 crimes per 1,000 people, although the majority of neighbourhoods had lower crime rates. The neighbourhoods with average or above average crime rates were located in the downtown core and the areas to the east and west of the downtown. The neighbourhoods with lower than average crime rates were located towards the outskirts of the city.

Figure 4

City of Calgary Crime Density for Total Crime



4.3 Logistic Regression Analysis Modeling Results

Commercial Robbery

Logistic regression analysis was used to predict whether distance to commercial robbery predicted childhood obesity. Three other independent variables were also included: median family income, proportion visible minority, and distance to parks. The omnibus test of model coefficients was statistically significant at $p < 0.001$, which allowed rejection of the null hypothesis that the overall model effects were zero. The Hosmer-Lemeshow Goodness of Fit test was not statistically significant at $p = 0.37$, which indicated that the model was not significantly different from a hypothetically perfect model and the model is, therefore, a good fit. As shown in Table 11, three of the independent variables were significantly related to the prediction of obesity: distance to commercial robbery (odds ratio = 0.87), median family income (odds ratio = 0.99), and proportion visible minority (odds ratio = 3.83). The odds ratio of 0.87 for the distance to commercial robbery variable showed that for every 1 kilometer a child lives farther away from a commercial robbery, the odds of obesity decreased by 13%. Distance to the closest park was not statistically significant based on the Wald's test, therefore this variable did not contribute significantly to the prediction of obesity.

Table 11

Commercial Robbery as a Predictor of Obesity, with Covariates

Predictor	Coefficient (*B*)	*p*	Odds Ratio	95% Confidence Interval
Distance to Commercial Robbery (km)	-0.143	0.003	0.867	[0.790, 0.952]
Median Family Income (thousands)	-0.010	0.000	0.990	[0.987, 0.993]
Proportion Visible Minority	1.344	0.000	3.833	[2.624, 5.599]
Distance to Closest Park (km)	-0.247	0.237	0.781	[0.519, 1.176]

Street Robbery

Logistic regression analysis was used to predict whether distance to street robbery predicted childhood obesity. Three other independent variables were also included: median family income, proportion visible minority, and distance to parks. The omnibus test of model coefficients was statistically significant at $p < 0.001$, which allowed rejection of the null hypothesis that the overall model effects were zero. The Hosmer-Lemeshow Goodness of Fit test was statistically significant at $p = 0.01$. This indicated that the model was significantly different from a hypothetically perfect model, and was therefore not a good fit. However, this test can be problematic with larger samples; as the sample size becomes larger the test detects smaller and smaller difference between observed and model –predicted values, therefore a significant result is more likely (Garson, 2011). Based on the results of the omnibus test of model coefficients, which showed that the model effects were not zero, and known concerns regarding the use of the Hosmer-Lemeshow Goodness of Fit test with larger samples, the results from this model should be interpreted with caution. As shown in Table 12, three of the independent variables significantly predicted obesity: distance to street robbery (odds ratio =

0.92), median family income (odds ratio = 0.99), and proportion visible minority (odds ratio = 3.49). The odds ratio of 0.92 for the distance to street robbery variable showed that for every 1 kilometer a child lived farther away from a street robbery, the odds of obesity decreased by 8%. Distance to the closest park was not statistically significant based on the Wald's test, therefore this variable did not contribute significantly to the prediction of obesity.

Table 12

Street Robbery as a Predictor of Obesity, with Covariates

Predictor	Coefficient (*B*)	*p*	Odds Ratio	95% Confidence Interval
Distance to Street Robbery (km)	-0.089	0.004	0.915	[0.861, 0.9473
Median Family Income (thousands)	-0.010	0.000	0.990	[0.987, 0.993]
Proportion Visible Minority	1.251	0.000	3.494	[2.346, 5.203]
Distance to Closest Park (km)	-0.237	0.254	0.789	[0.524, 1.186]

Assault

Logistic regression analysis was used to predict whether distance to assault predicted childhood obesity. Three other independent variables were also included: median family income, proportion visible minority, and distance to parks. The omnibus test of model coefficients was statistically significant at $p < 0.001$, which allowed rejection of the null hypothesis that the overall model effects were zero. The Hosmer-Lemeshow Goodness of Fit test was not statistically significant at $p = 0.31$, which indicated that the model was not significantly different from a hypothetically perfect model and the model is, therefore, a good fit. As shown in Table 13, two of the independent variables were significantly related to the prediction of obesity: median family income (odds ratio = 0.99), and proportion visible minority (odds ratio = 4.17). Distance to assault was not statistically significant based on the Wald's test. Therefore knowing whether the child lived closer to an assault did not better predict obesity than does looking at the proportion of obesity children in the population generally, or than would be expected by chance. Distance to the closest park was also not statistically significant based on the Wald's test.

Table 13

Assault as a Predictor of Obesity, with Covariates

Predictor	Coefficient (*B*)	*p*	Odds Ratio	95% Confidence Interval
Distance to Assault (km)	-0.150	0.196	0.861	[0.686, 1.081]
Median Family Income (thousands)	-0.010	0.000	0.990	[0.987, 0.993]
Proportion Visible Minority	1.429	0.000	4.174	[2.868, 6.075]
Distance to Closest Park (km)	-0.187	0.369	0.830	[0.552, 1.247]

Other Violence

Logistic regression analysis was used to predict whether distance to other violence predicted childhood obesity. Three other independent variables were also included: median family income, proportion visible minority, and distance to parks. The omnibus test of model coefficients was statistically significant at $p < 0.001$, which allowed rejection of the null hypothesis that the overall model effects were zero. The Hosmer-Lemeshow Goodness of Fit test was statistically significant at $p = 0.01$. This indicated that the model was significantly different from a hypothetically perfect model, and was therefore not a good fit. However, this test can be problematic with larger samples, as the sample becomes larger the test detects smaller and smaller difference between observed and model –predicted values, therefore a significant result is more likely (Garson, 2011). Based on the results of the omnibus test of model coefficients, which showed that the model effects were not zero, and known concerns regarding the use of the Hosmer-Lemeshow Goodness of Fit test with larger samples, the results from this model should be interpreted with caution. As shown in Table 14, three of the independent variables significantly predicted obesity: distance to other violence (odds ratio = 0.6), median family income (odds ratio = 0.99), and proportion visible minority (odds ratio = 3.45). The odds ratio of 0.6 for the distance to other violence variable showed that for every 1 kilometer a child lived farther away from another violence crime, the odds of obesity decreased by 40%. Distance to the closest park was not statistically significant based on the Wald's test, therefore this variable did not contribute significantly to the prediction of obesity.

Table 14

Other Violence as a Predictor of Obesity, with Covariates

Predictor	Coefficient (*B*)	*p*	Odds Ratio	95% Confidence Interval
Distance to Other Violence (km)	-0.516	0.000	0.597	[0.467, 0.763]
Median Family Income (thousands)	-0.010	0.000	0.990	[0.987, 0.993]
Proportion Visible Minority	1.253	0.000	3.499	[2.383, 5.138]
Distance to Closest Park (km)	-0.253	0.226	0.776	[0.515, 1.170]

Residential Break and Enter

Logistic regression analysis was used to predict whether distance to commercial break and enter predicted childhood obesity. Three other independent variables were also included: median family income, proportion visible minority, and distance to parks. The omnibus test of model coefficients was statistically significant at $p < 0.001$, which allowed rejection of the null hypothesis that the overall model effects were zero. The Hosmer-Lemeshow Goodness of Fit test was not statistically significant at $p = 0.25$, which indicated that the model was not significantly different from a hypothetically perfect model and the model is, therefore, a good fit. As shown in Table 15, two of the independent variables significantly predicted obesity: median family income (odds ratio = 0.99), and proportion visible minority (odds ratio = 4.30). Distance to residential break and enter was not statistically significant based on the Wald's test. Therefore knowing whether the child lived closer to a residential break and enter did not better predict obesity than did looking at the proportion of obese children in the population generally, or than would be expected by chance. Distance to the closest park was also not statistically significant based on the Wald's test.

Table 15

Residential Break and Enter as a Predictor of Obesity, with Covariates

Predictor	Coefficient (*B*)	*p*	Odds Ratio	95% Confidence Interval
Distance to Residential Break and Enter (km)	-0.480	0.056	0.619	[0.378, 1.013]
Median Family Income (thousands)	-0.10	0.000	0.990	[0.987, 0.993]
Proportion Visible Minority	1.458	0.000	4.297	[2.974, 6.209]
Distance to Closest Park (km)	-0.166	0.425	0.847	[0.564, 1.273]

Commercial Break and Enter

Logistic regression analysis was used to predict whether distance to commercial break and enter predicted childhood obesity. Three other independent variables were also included: median family income, proportion visible minority, and distance to parks. The omnibus test of model coefficients was statistically significant at $p < 0.001$, which allowed rejection of the null hypothesis that the overall model effects were zero. The Hosmer-Lemeshow Goodness of Fit test was not statistically significant at $p = 0.06$, which indicated that the model was not significantly different from a hypothetically perfect model and the model is, therefore, a good fit. As shown in Table 16, two of the independent variables significantly predicated obesity: median family income (odds ratio = 0.99), and proportion visible minority (odds ratio = 4.39). Distance to commercial break and enter was not statistically significant based on the Wald's test. Therefore knowing whether the child lived closer to commercial break and enter did not better predict obesity than does looking at the proportion of obesity children in the population generally, or than would be expected by chance. Distance to the closest park was also not statistically significant based on the Wald's test.

Table 16

Commercial Break and Enter as a Predictor of Obesity, with Covariates

Predictor	Coefficient (*B*)	*p*	Odds Ratio	95% Confidence Interval
Distance to Commercial Break and Enter (km)	-0.143	0.247	0.867	[0.681, 1.104]
Median Family Income (thousands)	-0.10	0.000	0.990	[0.987, 0.993]
Proportion Visible Minority	1.478	0.000	4.386	[3.038, 6.330]
Distance to Closest Park (km)	-0.203	0.334	0.817	[0.541, 1.232]

Theft of Vehicle

Logistic regression analysis was used to predict whether distance to theft of vehicle predicted childhood obesity. Three other independent variables were also included: median family income, proportion visible minority, and distance to parks. The omnibus test of model coefficients was statistically significant at $p < 0.001$, which allowed rejection of the null hypothesis that the overall model effects were zero. The Hosmer-Lemeshow Goodness of Fit test was not statistically significant at $p = 0.11$, which indicated that the model was not significantly different from a hypothetically perfect model and the model is, therefore, a good fit. As shown in Table 17, three of the independent variables significantly predicted obesity: distance to theft of vehicle (odds ratio = 0.68), median family income (odds ratio = 0.99), and proportion visible minority (odds ratio = 3.94). The odds ratio of 0.68 for the distance to theft of vehicle variable shows that for every 1 kilometer a child lives farther away from theft of vehicle, the odds of obesity decreases by 32%. Distance to the closest park was not statistically significant based on the Wald's test, therefore this variable did not contribute significantly to the prediction of obesity.

Table 17

Theft of Vehicle as a Predictor of Obesity, with Covariates

Predictor	Coefficient (*B*)	*p*	Odds Ratio	95% Confidence Interval
Distance to Theft of Vehicle (km)	-0.387	0.024	0.679	[0.486, 0.949]
Median Family Income (thousands)	-0.009	0.000	0.991	[0.988, 0.993]
Proportion Visible Minority	1.371	0.000	3.941	[2.697, 5.760]
Distance to Closest Park (km)	-0.177	0.391	0.838	[0.558, 1.256]

Theft from Vehicle

Logistic regression analysis was used to predict whether distance to theft from vehicle predicted childhood obesity. Three other independent variables were also included: median family income, proportion visible minority, and distance to parks. The omnibus test of model coefficients was statistically significant at $p < 0.001$, which allowed rejection of the null hypothesis that the overall model effects were zero. The Hosmer-Lemeshow Goodness of Fit test was not statistically significant at $p = 0.42$, which indicated that the model was not significantly different from a hypothetically perfect model and the model is, therefore, a good fit. As shown in Table 18, two of the independent variables significantly predicted obesity: median family income (odds ratio = 0.99), and proportion visible minority (odds ratio = 4.34). Distance to theft from vehicle was not statistically significant based on the Wald's test. Therefore knowing whether the child lived closer to theft from vehicle did not better predict obesity than does looking at the proportion of obesity children in the population generally, or than would be expected by chance. Distance to the closest park was also not statistically significant based on the Wald's test.

Table 18

Theft from Vehicle as a Predictor of Obesity, with Covariates

Predictor	Coefficient (*B*)	*p*	Odds Ratio	95% Confidence Interval
Distance to Theft from Vehicle (km)	-0.364	0.253	0.695	[0.373, 1.296]
Median Family Income (thousands)	-0.010	0.000	0.990	[0.987, 0.992]
Proportion Visible Minority	1.467	0.000	4.335	[2.999, 6.265]
Distance to Closest Park (km)	-0.171	0.413	0.843	[0.560, 1.269]

Chapter 5: Discussion

5.1 The Influence of Crime on Childhood Obesity

The aim of this study was to investigate the association between the BMI of preschool children and neighbourhood crime, after controlling for socioeconomic factors and distance to the nearest park or green space. Personal choices have long been seen as the primary way to combat what is often referred to as 'the childhood obesity epidemic' (Ebbeling, Pawlak, & Ludwig, 2002). However, there is a growing realization that children's environments also influence obesity (Ebbeling et al., 2002).

In this study, the rate of childhood obesity in Calgary was lower than national rates. National BMI percentile rates for 3- to 5-year-olds were 2.5% underweight, 65.5% were normal weight, 17.5% were overweight and 14.5% were obese (Statistics Canada, 2012b). Of the study sample, which included children aged 4- to 7-years, 4.4% of the children were underweight, 74.7% were normal weight, 12.4% were overweight and 8.5% were obese. The difference between the Calgary and the national rates of obesity raises questions about how the results of this study generalize nationally. The year of data collection (2011) and how measurements were taken were the same between the two samples; however, the national sample was slightly younger than the Calgary sample (3- to 5-year-olds versus 4- to 7-year-olds) (Statistics Canada, 2012b). Previous studies have shown that rates of obesity in Canadian children decrease from east to west with Alberta having one of the lowest rates of childhood obesity in Canada (Shields & Tjepkema, 2006; Willms, Tremblay, & Katzmarzyk, 2003). Willms et al. (2003) also found that the risk of being overweight was more related to a child's geographical location than demographic variables including income, parental education and number of siblings. The lower rates of childhood obesity seen in this study, compared to national rates, are in keeping with previous research, however why there seems to be geographical variation across Canada is unclear.

In terms of crime in Calgary, 19,275 crimes were committed in the year 2011, with the majority being property crimes. A comparison of national and Alberta rates from Statistics Canada showed Alberta generally had lower rates of attempted murder and break and enter, but higher rates of homicides, major assaults, robbery, and motor vehicle crimes, than did Canada as a whole (Brennan, 2012). Statistics Canada used slightly different categories of crime, so direct comparisons of all crime categories could not be made between national data and the Calgary data used in the current study. However, from the current study, Calgary's rate of break and enter is slightly lower than both the Alberta and the national rates (Brennan, 2012). The rate of assault was, however, higher than Alberta and national rates (Brennan, 2012). Nationally, in Alberta, and in the current study, rates of property crime were much higher than rates of person crimes (Brennan, 2012).

Bronfenbrenner's bioecological model was used as a way to theoretically understand this study as this model places a child's development within a system of relationships and multiple levels of interactions with their environment (Bronfenbrenner, 1994). In the discussion of childhood obesity, how children interact with their family, peers, school, built environment, and the policies and practices that influence all of these factors, are important to investigate, yet can be difficult to integrate. Bronfenbrenner's bioecological model allows these factors to be situated within the child's wider environment. The results of this study are best understood in the *macrosystem* level of the model as this level refers to the overlaying policies that influence a child's life. This study did not look at specific victims of crime, but at crime rates. Therefore, the crime that is discussed within this study does not directly influence children, or their families, but is acting on children's lives indirectly. The *exosystem* level highlights aspects of structures within the microsystem, rather that direct effects on the individuals history (Bronfenbrenner, 1994) and is also important in understanding why some categories of crime predicted obesity and some did not.

Children who were obese lived closer to certain types of crimes than did children of normal weight, although these calculations were not adjusted for socioeconomic covariates. It is hard to draw conclusions without controlling for socioeconomic differences, as socioeconomic factors influence both childhood obesity (Magnusson et al., 2011; Singh et al., 2008) and crime (Lange et al., 2011). However, this general trend does start to give insight into the effects of different categories of crime. This research is novel in the depth to which the crime variable was examined. In contrast to previous research that treated crime as a single undifferentiated variable (Lange et al., 2011; Miranda et al., 2012; Sakai, 2013), or simply used the homicide rate as a proxy for all crime (Burdette & Whitaker, 2004; Lovasi et al., 2011; Lovasi et al., 2013; Sandy et al., 2013), this study separated crime into two types with four categories of crime in each type. Detailed categorization of crime is important because fear of crime generally depends on a person's perception of becoming a victim and on how serious the consequences of victimization are likely to be (Hale, 1996). Although this study did not address perceptions of crime, total crime may not accurately reflect the variety of outcomes from different categories of crime. For example, Carroll-Scott et al. (2013), who separated crime into property crime and violent crime, found that property crime was associated with a higher BMI in adolescents, but that violent crime was not, which was hypothesized to be due to social ties. While these results did not mirror those of the current study, it reinforces the need to study categories of crime separately, rather than assuming that crime is one homogeneous variable.

The neighbourhoods with average or above average crime rates were located in the downtown core and the areas to the east and west of the downtown. The neighbourhoods with lower than average crime rates were located towards the outskirts of the city. The analysis showed that commercial robbery, street robbery, other violence, and theft of vehicle predicted obesity. Theft of a vehicle is a type of property crime that could have implications for the person in terms of quality of life, which was speculated to be why it was associated with childhood obesity. In some ways a vehicle could be thought of as an extension of ourselves, so theft of a vehicle could be taken very personally. The person crimes target a specific person, which can cause mental, physical and financial hardship for that person, as well as their family, for what may be a long period of time (Brennan, 2011). It can cause financial and physical difficulties for families, such as if the insurance company does not cover the full replacement cost or if other modes of travel, such as walking or taking the bus, are required. These speculations are based on the notion described by Tulloch (2004) that the implications rather than the likelihood of a crime is what influences a parent's concern regarding crimes, as parents report they could never forgive themselves if a crime affected their child. Hale (1996) also found that one of the major influences on a person's fear of crime is their feelings of vulnerability. So crimes that increase feelings of vulnerability, or that have greater implications, such as commercial robbery, street robbery, other violence, and theft of vehicle, are likely to create the most worry for people. The association between crimes that affect families' quality of life highlights how factors at the *exosystem* and *macrosystem* levels of Bronfenbrenner's bioecological model (Bronfrenbrenner, 1986) affect children through indirect means. No research appears to suggest a direct causal relationship between childhood obesity and crime. However, previous research on the effects of the perception of crime, coupled with the results from the current study, and overlaid on an understanding of Bronfenbrenner's bioecological model, start to illustrate the complex associations that influence childhood obesity.

Of the eight studies included in the literature review, four studies showed a positive association between childhood obesity and certain types of neighbourhood crime (Carroll-Scott et al., 2013; Lovasi et al., 2013; Miranda et al., 2012; Sandy et al., 2013), and four (Burdette & Whitaker, 2004; Grafova, 2008; Lange et al., 2011; Sakai, 2013) showed no association. These studies are, however, difficult to compare to the current study as each used a single measure of crime, either homicide rate or total crime. The current study found that some categories of crime were predictive of childhood obesity and some were not, so it is hard to know whether some of the previous research on this topic failed to find an association between childhood obesity and crime because it was obscured by the use of a single measure of crime, rather than multiple categories. Carroll-Scott et al. (2013) separated crime into violent crime and property crime and found that living in neighbourhoods with more property crime was associated with obesity, though this was not the case for neighbourhoods with higher rates of violent crime. These are not the same crime categories used in the current study, but the current study did find that the majority of the person crimes, which include a measure of violent crime, were predictive of obesity, which is contrary to what Carroll-Scott et al. (2013) found. The only study from previous literature that found similar results to the current study was Miranda et al. (2012), which found that property disorder, nuisances, violent crime, and total crime were significantly associated with increased BMI levels. While overall the results from the current study did not appear to reflect what had been found in previous studies, a direct comparison is very difficult due to the use of different measures of crime and different densities of crime in different cities and countries.

Assault was the only person crime category that was not predictive of childhood obesity, possibly as people feel their personal risk of assault is within their control and that the long-term implication of assault is lower than for other crime categories strangers (Hipp & Roussell, 2013). Assault is a person crime, and could be said to share many of the same impacts as the categories of crime that were associated with obesity, yet assault was not found to predict obesity. This was an unexpected result, with no clear explanation. Assault was the most prevalent type of person crime, and this category included less homogeneous crimes. Assaults are different from most other categories of crimes as they usually occur between people who know each other, rather than strangers (Hipp & Roussell, 2013), though domestic violence was excluded from the current study. As mentioned earlier one of the major conclusions from research regarding what drives a person's fear of crime, is their feelings of vulnerability (Hale, 1996). Therefore, the predictive ability of assault on childhood obesity may not be significant as people feel that their personal risk of assault is within their control. It is also possible that instances of assault may be less severe than other person crimes, including those in the other violence category, indicating that some instances of assault do not exert a long-term impact or are not discussed among friends and family. As the implications of a crime may play into the level of worry about this crime (Tulloch, 2004), assault may not be predictive of childhood obesity as people feel this category of crime has fewer long-term impacts.

5.2 What the Covariates Add

Neighbourhood level median family income and the proportion of the population who self-identify as visible minorities were significant contributors to all the models predicting childhood obesity. Other research has shown that higher childhood obesity rates tend to be associated with lower income families, lower family education, and residence in neighbourhoods with higher percentages of visible minorities (Magnusson et al., 2011; Singh et al., 2008). Of particular note was a large systematic review of studies looking at childhood obesity and socioeconomic indicators by Shrewsbury and Wardle (2008). In their review, the association between income and obesity was included in 11 studies, with four studies finding an inverse association, three finding no association, and four finding a variable association (Shrewsbury & Wardle, 2008). There was an inverse association seen between ethnicity and obesity, although this association was also inconsistent across studies (Shrewsbury & Wardle, 2008). While the review does support the association seen in the current study between family income and childhood obesity, as well as between visible minorities and childhood obesity, the review illustrates that these relationships are complicated and that there are likely other factors influencing childhood obesity (Shrewsbury & Wardle, 2008).

Distance to the closest park was not a statistically significant predictor of obesity for any of the crime categories. Children who were obese lived slightly closer to parks and green spaces than children of a normal weight, before socioeconomic factors were controlled for. This result was also seen in a study by Potestio et al. (2009), which showed that childhood obesity was not associated with access to parks and green spaces. However, other studies have shown that greater availability of parks and green space decreased obesity rates in children (Wolch et al., 2011). This indicates that while the results from the current study are not totally unexpected based on previous research, the overall association between childhood obesity and distance to green space is neither definite nor well understood.

5.3 Perception of Crime versus Actuality of Crime

While this study looked for an association between childhood obesity and crime, a direct correlation was in no way implied. There are a number of factors that may filter the effect that crime has on the children, including perception of safety. In this discussion perceived safety is a general term regarding neighbourhood factors more wide reaching than crime, including traffic safety (Durand et al., 2012). Perceived crime is an emotional response to the possibility of crime (Lorenc et al., 2012). Fear of crime is how worried people are about specifically becoming a victim of crime (Lorenc et al., 2012). However, perceived crime and fear of crime are both encompassed in perception of safety. Crime is related to perceived safety and fear of crime, and certainly plays into how these perceptions are formed (Durand et al., 2012; Hale, 1996), but crime is an actuality whereas perception of safety and fear of crime are personal constructs. This study looked at actual crime only; however, future research regarding perceived safety and fear of crime may help to better understand the study results.

Research on the perception of crime is pertinent in this discussion as it also highlights some of the possible influencing factors and may help to explain some of the results seen. Fear of crime has been found to be influenced by an individual's perception of becoming a victim and on the seriousness of the consequences of victimization (Hale, 1996). Hale (1996) also found a stronger relationship between the incidence of fear of crime and hearing about crimes from friends or neighbours, rather than in the media. In addition to hearing about crimes from friends and neighbours though, media reports of local crimes can also lead to increased fear of crime

(Hale, 1996). The crime categories in the current study that were associated with childhood obesity were speculated to be types of crimes that would likely be portrayed in the media and discussed among neighbours and friends, as they are likely to have consequences, often serious, on the victims and their families. News media have also been shown to focus extensively on violent crime (Busselle, 2003), although this is the least prevalent type of crime. The similarities between the results of this study and previous results regarding perceptions of safety and fear of crime, raise the possibility that the association between crime and childhood obesity is closely tied to, or filtered through, the perception of crime. However, Carroll-Scott et al. (2013) and others (Lorenc et al., 2012) found that subjective measures of perceptions of safety had no association with BMI. The role of altruistic fear may also play a part in this relationship. Specifically, parents are more likely to fear for the safety of their children than for themselves (Busselle, 2003; Warr & Ellision, 2000), so it is possible that as parents become victims of crime, or hear about crimes through friends, neighbours and the media, their fear of their children becoming victims of crime may increase, thus causing them to make changes to routines that may in turn make their children more prone to obesity.

5.4 Limitations

Obesity is complex with many influencing factors from many areas of the child's life (Lumeng et al., 2006). Income and neighbourhood ethnic makeup, as socioeconomic factors, were controlled for on a neighbourhood basis using available Census data. Data regarding other factors that may influence obesity, such as physical activity, maternal obesity, and food choices, were not available in the original BMI dataset, and were not as readily available as the census data, therefore they were not controlled for, which limits the study.

There was also the possibility of misclassifying children's BMI, as levels of physical fitness, ethnic origin, frame size, and biological maturation were not taken into account (Colman et al., 2010). For example, enhanced muscular development as lean body mass was not distinguished from fat mass, a large head size, and a high torso-to-leg ratio (Colman et al., 2010). The fact that healthy weight children may have been misclassified as overweight was one of the factors that contributed to the decision to include only children who were obese in the logistic regression modeling. However, BMI is an internationally accepted way to measure and compare rates of overweight and obese children, making it an important metric in charting both the rising childhood obesity (Miranda, Edwards, Anthopolos, Dolinsky, & Kemper, 2012) and its long-term health consequences (Akhtar-Danesh, Dehghan, Morrison, & Fonseka, 2011).

There is the possibility of misclassification in the BMI data set however. For instance, a child's postal code in the database may not adequately reflect their address when the BMI measurements were taken. If children had their BMI measurement taken at one clinic visit, then moved, and later returned to the clinic, their postal code would have been be updated to reflect their new address. Only the new postal code would remain associated with their BMI data, allowing the possibility of some inaccuracies within these data.

There are inherent limitations stemming from the use of geographic data including the use of neighbourhood level census data, and from the challenges of mapping both crime locations and children's residential postal codes. This study used neighbourhood level census data as a proxy for individual level data regarding family income, proportion visible minority and education level. There are indications that neighbourhood level variables can change depending on how the boundaries of neighbourhoods are determined, referred to as the modifiable areal unit problem (Kwan, 2012). This is due to the fact that arbitrarily determined boundaries often contain several distinct neighbourhoods (Kruger, 2008), and social context and relationships are not geographically derived and often occur in different geographic areas (Kwan, 2012). Therefore, the degree of homogeneity in an area determines the degree to which the area level variables represent the individual level variables. For the City of Calgary, neighbourhoods have been found to be reasonable proxies for individual variables as the neighbourhood boundaries were constructed based on social, historical and geographical criteria (Gauvin et al., 2007); therefore, neighbourhood level variables were used for this study. There is evidence from a Nova Scotia study that reported similar results when comparing individual and neighbourhood data to look at socioeconomic status (Joseph et al., 2006). There were also indications that multilevel modeling may be a more correct type of modeling to use when looking at the impact of neighbourhood factors on health (Pickett & Pearl, 2001). People from the same neighbourhood seem to be more alike than people from different neighbourhoods, which can lead to a violation of the independence assumption in non-hierarchical models (Pickett & Pearl, 2001). Also, cross sectional studies, such as the current study, do not give definite information about cause and effect relationships as they offer only information about a single moment in time (Katz, 2011). Therefore, in the current study, there is no way to know if obese children were move likely to live in, or move to, certain areas, or if certain areas lead to obesity, which should be considered when discussing the results of the current study. Analysis that controls for clustering would be one way to investigate this, however, the overall design of a cross-sectional study does not allow for any speculation about causation. Furthermore, there are no known studies regarding how long it takes for a neighbourhood factor to produce obesity, though it could be speculated that this process takes a longer period of time. Therefore looking at data regarding crime and obesity of the same year, as was done in the current study, may be misleading. Future studies could control for this by including both crime and obesity data from multiple years.

There are also limitations of the study as a result of the use of data collected for another purpose. This particular dataset was collected from immunization clinic visits and therefore, children who did not attend these clinics were excluded, and may contribute to selection bias. Previous research has shown that these children may be of lower socioeconomic status and may be from ethnic minorities (Potestio et al., 2009). Lower socioeconomic status has been shown to be significantly associated with a higher BMI in children (Magnusson et al., 2011) and some studies have shown that cultural factors may play a role in childhood obesity (Magnusson et al., 2011). Therefore, the exclusion of children who did not attend immunization clinics may underestimate the relationships found in this study as the sample may not be representative of the whole population and may have a bias towards those with higher incomes.

Multiplicity can occur when statistical tests are used repeatedly, which increases the potential for Type I errors, or the possibility of differences between dependent and independent variables emerging simply by chance (Goldman, 2008). This was a possibility in the current study as eight categories of crime were tested with an individual logistic regression model. The Bonferroni correction was considered, however as there were only three covariates in each model, it was considered unnecessary (Nakagawa, 2004). Also, the Bonferroni correction can sometime be too conservative, leading to a high rate of false negatives (Nakagawa, 2004). Therefore, it was possible that multiplicity affected the results of the current study.

Further, misclassification was possible if either the children's residential postal code, or a crime location postal code, could not be mapped. The postal codes that could not be mapped were recently created postal codes for new neighbourhoods that had not yet been entered in the

Postal Code Registry file, or postal codes that may not have been entered correctly in the data capture process. This meant that data were lost from both the BMI dataset and the crime dataset, although no statistically significant difference was found between the children who were excluded and those who were included. There is also some question as to how closely the postal code location and the actual location align. Postal codes assign one set of latitude and longitude coordinates to every location within that postal code area, but some locations may not be well approximated by the postal code. Previous research in Calgary showed, however, that over 80% of postal code locations were within 200m of the actual residential location (Bow et al., 2004). While this seems like a large distance, Bow et al. (2004) felt that postal codes were a reasonable proxy for residential location in most health research and postal codes have been used in this type of research previously (Lovasi et al., 2013). Future studies should focus on decreasing this mis-alignment of location through using more accurate ways of locating both children's residences and crime locations, such as by using street addresses. The fact that this was not a possibility with the available datasets as street addresses were not available is a limitation of this study. When discussing very small differences in how close obese children and normal weight children lived to crime categories, the fact that 20% of the postal codes may be more than 200m away from the actual residence could have influenced results in some cases.

Finally, this study is limited by the fact that interactions between the crime categories and the covariates were not tested. There was no theoretical basis upon which to test interactions, as the specific crime categories used in this study have never been used in this type of analysis. However, the study results would have been strengthened by knowing that the crime categories and the covariate terms did not interact.

5.5 Implications and Future Directions

Theoretical

This research adds to a limited body of research, therefore the majority of the implications and future directions are theoretical, rather than clinical. Firstly, this study should be replicated in other Canadian and international cities. This would allow researchers to examine similarities and differences in the outcomes to determine if cities differ in the influence of crime on childhood obesity levels, and if so, how they differ. For instance, if an incidence of a certain type of crime is associated with increased obesity rates in one city but not in another, an examination of the policies and practices of both urban design and city planning in those cities could be undertaken to understand their different relationship within the model. Secondly, additional research should be done that includes more of the variables potentially linked to childhood obesity, such as maternal BMI and physical activity. Future studies should also include more individual level variables, such as family income. These recommendations are based on reflections of the current study. However, they are also reinforced by comments from Shrewsbury and Wardle (2008) recommending that future studies of childhood obesity incorporate more than one socioeconomic measure wherever possible at both the household and neighbourhood level.

Currently there are very few studies looking at the association between childhood obesity and crime, especially in the Canadian context. Yet, city planners, health regions, police departments and parents need to be aware of the possibility of an association between childhood obesity and crime. The US based Urban Land Institute recently released a toolkit for developers, property managers and designers of real estate developments, which focuses on enhancing health through changes in approaches to architecture, land development and city planning (Urban Land

Institute, 2015). While this toolkit discusses many evidence informed opportunities to improve health through changes in the built environment, there was no mention of crime and the role it possibly plays (Urban Land Institute, 2015). The document, which is aimed at urban design professionals, indicates significant interest in how the built environment influences health (Urban Land Institute, 2015). Clearly this avenue of research needs to include an understanding of the role that crime plays in this health and built environment system.

Clinical

While this study found an association between childhood obesity and certain categories of crime, a causal relationship was in no way implied. There are a number of factors in the chain, which may filter the effect that crime has on children, including perception of safety. Obesity is also highly complex with many influencing factors from many areas of a child's life, including diet and physical activity (Lumeng et al., 2006). There is an increasing recognition that the built environment plays a role in health, including by influencing obesity rates in adults and children (Ebbeling et al., 2002; Urban Land Institute, 2015). Public health professionals who are considering population-based interventions to reduce childhood obesity, and to improve health generally through built environment changes, need to be aware of the possibility that crime is another factor that influences childhood obesity. Therefore, multi-disciplinary teams, including police representatives, should guide these interventions. Educating parents is also an important individual level clinical implication of the current study. Public health professionals are uniquely placed to help educate parents about the realities of crime, including what the crime risks for children actually are in their city as parental perceptions about safety are often disproportionate to actual dangers (Brussoni, Olsen, Pike, & Sleet, 2012). For example, nearly a third of Canadian children are currently overweight or obese (Active Healthy Kids Canada, 2012), yet many of the crime related concerns expressed by parents, such as abductions, are extremely rare events (Brussoni et al., 2012). Increasing discussion of the possible association between childhood obesity and crime by public health professionals is needed in both population health and individual level programming.

5.6 Conclusion

This study looked at whether actual crime was associated with the BMI of children aged 4 to 5 years living in Calgary, Canada, and identified some associations, both geographically through GIS analysis, and through statistical analysis. This study showed that commercial robbery, street robbery, other violence, and theft of vehicle were associated with childhood obesity. The study also contributes to an expanding dialogue about how aspects of the built environment, such as crime, influence the health of children through obesity. It is important for children's health and well-being that they are physically active outside (Brussoni et al., 2012), so factors that change behaviours and reduce children's physical activity need to be discussed at the broad societal level (Sandy et al., 2013). The hope is that this study contributes in some small way to this goal.

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Appendix A: Definitions

Bayesian Model of Pedestrian Walking Distance: is a distance of 0.25 miles. Which is "the point at which the rate of change of the slope of the probability distribution of walking distance or a function of walking distance is greatest" dependent on trip type, trip purpose and time of day (Seneviratne, 1985).

Body Mass Index (BMI): is calculated by dividing a child's weight in kilograms by their height in metres squared (Centers for Disease Control and Prevention, 2011).

Built Environment: the "physical infrastructure (e.g., buildings, roads, and lighting) and outdoor spaces (e.g., parks and urban design) of a place, as well as the policies that shape them" (Miranda et al., 2012, p. 750).

Child: a young human being below the age of puberty or below the legal age of majority (Oxford Dictionary, 2013a). However, this study looks specifically at children between the ages of 4 and 7 years old.

Crime: an action or omission which constitutes an offence and is punishable by law (Oxford Dictionary, 2013b).

Environment: "everything outside the person, in contrast with individual, or personal variables" (Story, Kaphingst, Robinson-O'Brien, & Glanz, 2008, p. 254).

Geocoding: when a reference map is paired with the address of something (Palombaro, 2011).

Geographical Information System (GIS): A geographic information system (GIS) integrates hardware, software, and data for capturing, managing, analyzing, and displaying all forms of geographically referenced information (Ersi, 2013).

Overweight and Obese: to determine if a child is overweight or obese from their BMI calculation, the child's BMI is plotted, versus the child's age, on a gender specific, standardized growth chart. The percentile within which the child's BMI falls determines their weight status. The BMI classifications from the Centers for Disease Control are as follows (Centers for Disease Control and Prevention, 2011):

- BMI less than the 5th percentile is classified as 'underweight'
- BMI over the 5th percentile and less than the 85th percentile represents a 'healthy weight'
- BMI between the 85th percentile and less than the 95th percentile is classified as 'overweight'
- BMI equal to or greater than the 95th percentile is classified as 'obese'

Policies: "laws, regulations, policymaking actions, or formal and informal rules established by government or formal organizations" (Story et al., 2008, p. 254).

Spatial analysis: the techniques and tools that form geographic information systems (GIS), associated software and geographical modeling techniques (de Smith, Goodchild, & Longley, 2013).

Appendix B: Logistic Regression Assumption Testing

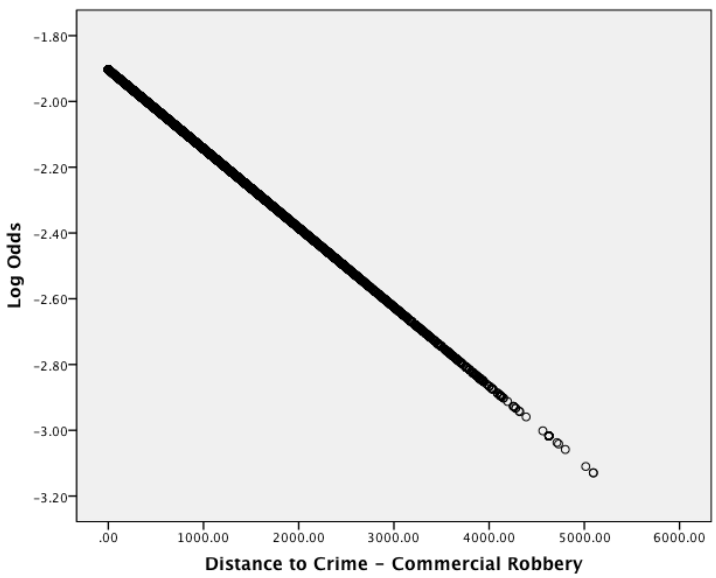
Linearity

To check if the variables meet the assumption of a linear relationship (linearity) inherent in the logistic regression analysis. All variables were found to be linear.

Commercial Robbery

Graph B1

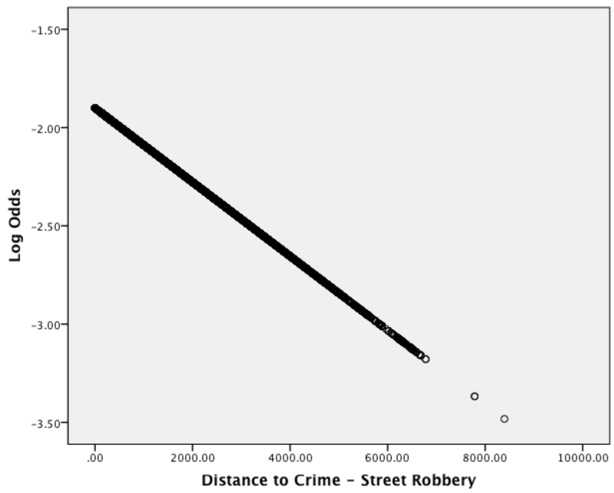
Log Odds of Obesity versus Distance to Commercial Robbery (m)



Street Robbery

Graph B2

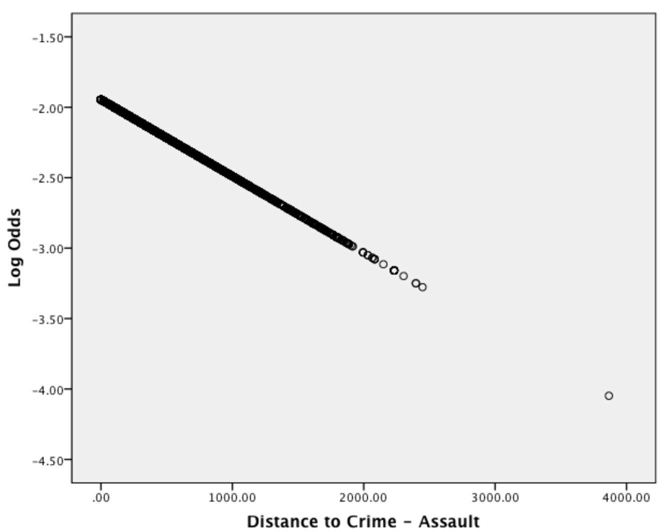
Log Odds of Obesity versus Distance to Street Robbery



Assault

Graph B3

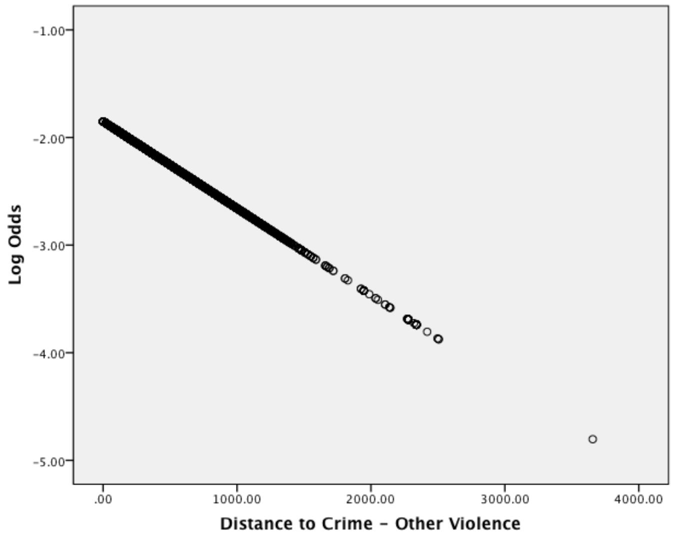
Log Odds of Obesity versus Distance to Assault



Other Violence

Graph B4

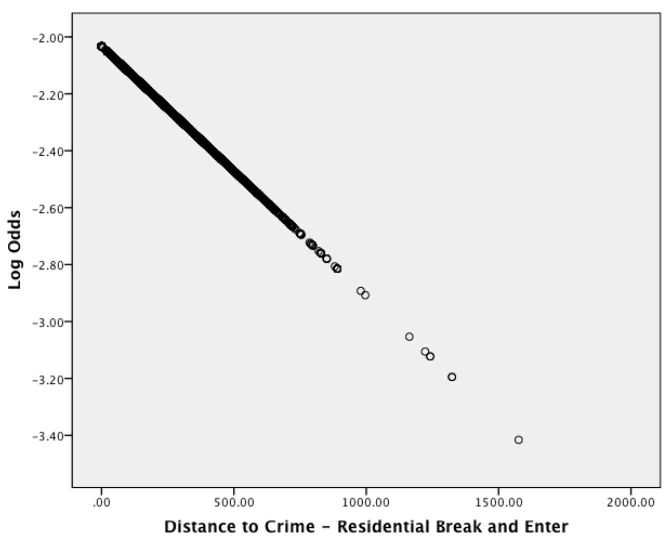
Log Odds of Obesity versus Distance to Other Violence



Residential Break and Enter

Graph B5

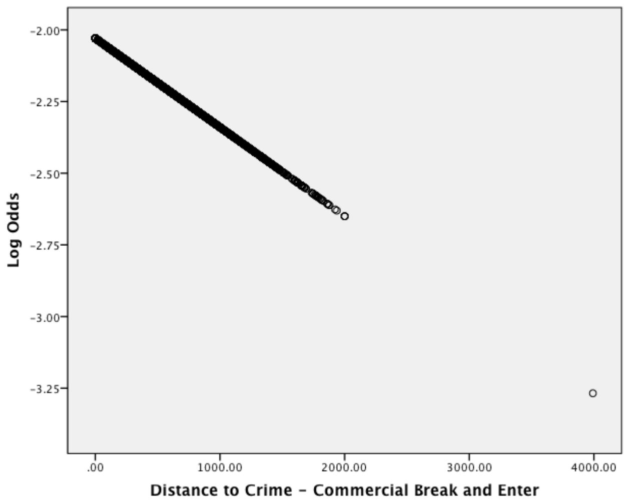
Log Odds of Obesity versus Distance Residential Break and Enter



Commercial Break and Enter

Graph B6

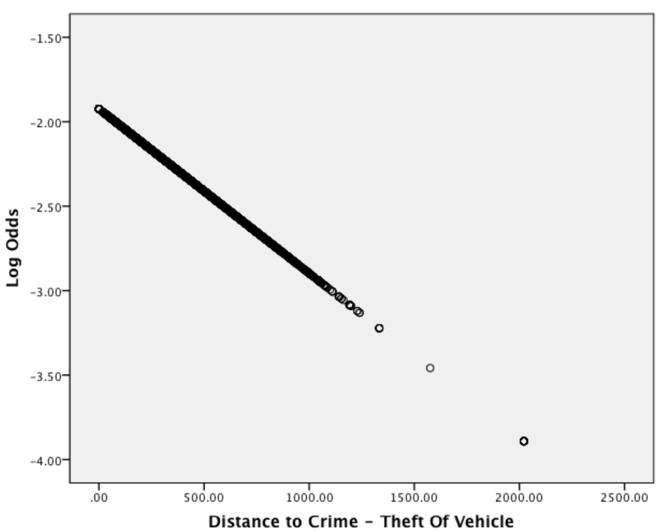
Log Odds of Obesity versus Distance to Commercial Break and Enter



Theft of Vehicle

Graph B7

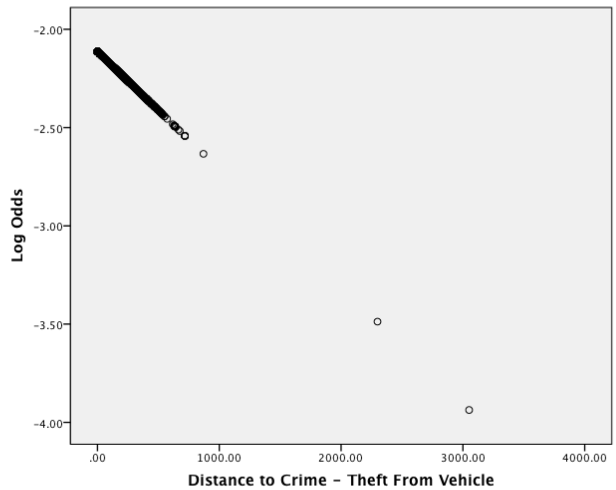
Log Odds of Obesity versus Distance to Theft of Vehicle



Theft From Vehicle

Graph B8

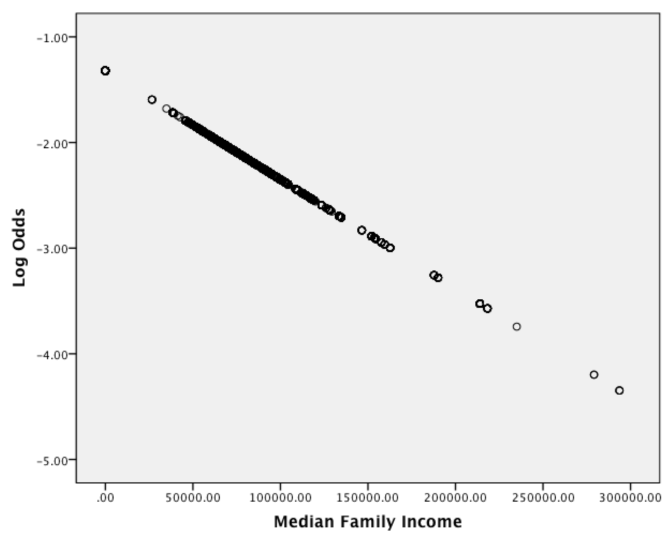
Log Odds of Obesity versus Distance to Crime – Theft from Vehicle



Median Family Income

Graph B9

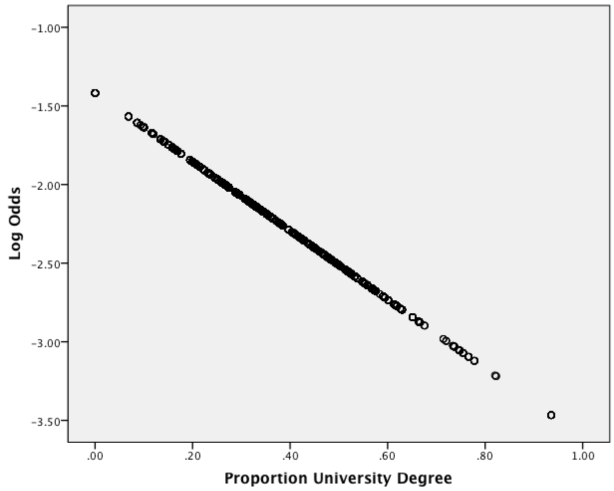
Log Odds of Obesity versus Median Family Income



Proportion of the Neighbourhood with a University Degree

Graph B10

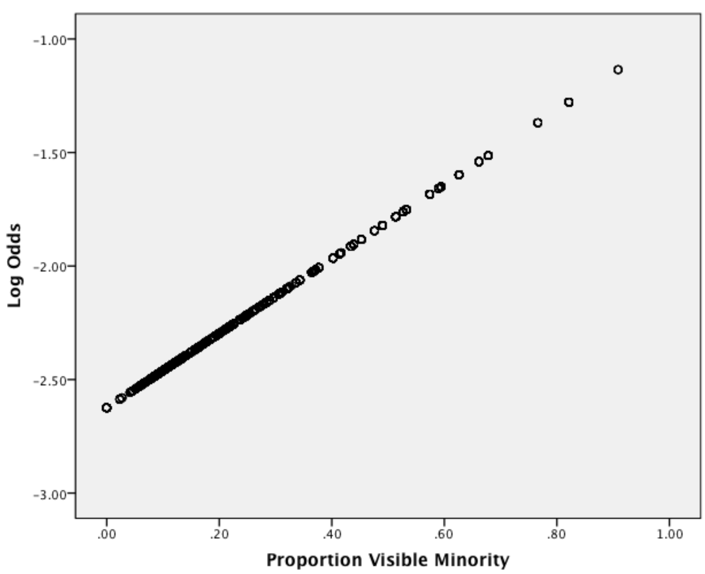
Log Odds of Obesity versus Proportion of the Neighbourhood with a University Degree



Proportion of the Neighbourhood who is a Visible Minority

Graph B11

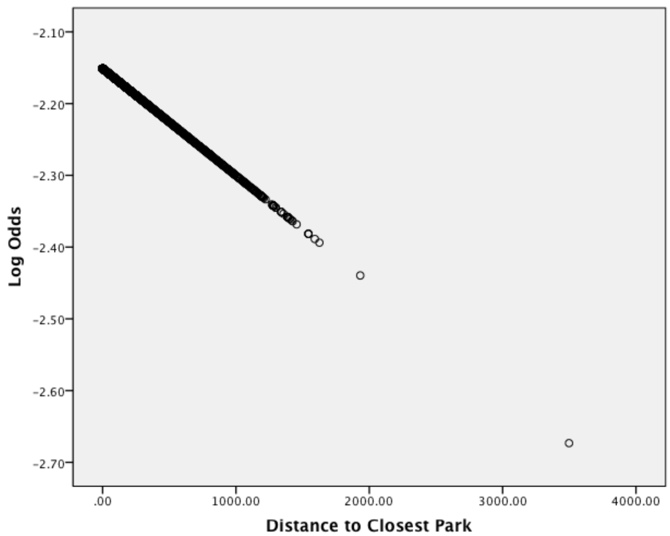
Log Odds of Obesity versus Proportion of the Neighbourhood who is a Visible Minority



Distance to Closest Park

Graph B12

Log Odds of Obesity versus Distance to Closest Park



Interactions

Table B1

Interactions Between Covariates

	Distance to the closest park in meters	Median family income	Proportion of the neighbourhood who is a visible minority
Distance to the closest park in meters	--	Not Significant	Not Significant
Median family income	--	--	Not Significant
Proportion of the neighbourhood who is a visible minority	--	--	--

Multicollinearity

Table B2

Correlations Between Weight Category, Crime Category and Covariates

	BMI	Parks	Commercial B&E	Commercial Robbery	Other Violence	Residential B&E	Street Robbery	Theft FROM Vehicle	Theft OF Vehicle	Assaults	Visible Minority Proportion	Some University Proportion	Median Income
BMI	1	-0.008	-0.029	-0.056	-0.069	-0.039	-0.069	-0.02	-0.065	-0.054	0.096	-0.104	-0.086
Parks	-0.008	1	-0.152	-0.123	-0.071	-0.017	-0.116	0.02	-0.054	-0.101	-0.104	0.136	-0.08
Commercial B&E	-0.029	-0.152	1	0.231	0.154	0.168	0.196	0.111	0.252	0.187	0.001	0.139	0.196
Commercial Robbery	-0.056	-0.123	0.231	1	0.384	0.2	0.531	0.07	0.361	0.362	-0.169	0.134	0.125
Other Violence	-0.069	-0.071	0.154	0.384	1	0.137	0.267	0.113	0.316	0.295	-0.241	0.169	0.097
Residential B&E	-0.039	-0.017	0.168	0.2	0.137	1	0.192	0.193	0.232	0.171	-0.075	0.199	0.163
Street Robbery	-0.069	-0.116	0.196	0.531	0.267	0.192	1	0.1	0.352	0.335	-0.323	0.149	0.156
Theft FROM Vehicle	-0.02	0.02	0.111	0.07	0.113	0.193	0.1	1	0.163	0.113	-0.072	0.064	0.029
Theft OF Vehicle	-0.065	-0.054	0.252	0.361	0.316	0.232	0.352	0.163	1	0.429	-0.214	0.358	0.296
Assaults	-0.054	-0.101	0.187	0.362	0.295	0.171	0.335	0.113	0.429	1	-0.168	0.341	0.349
Visible Minority Proportion	0.096	-0.104	0.001	-0.169	-0.241	-0.075	-0.323	-0.072	-0.214	-0.168	1	-0.174	-0.116
Some University Proportion	-0.104	0.136	0.139	0.134	0.169	0.199	0.149	0.064	0.358	0.341	-0.174	1	0.777
Median Income	-0.086	-0.08	0.196	0.125	0.097	0.163	0.156	0.029	0.296	0.349	-0.116	0.777	1

Note. Correlations that are significant are highlighted in blue. B&E = break and enter