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AN ANALYSIS OF COLLECTIVE EFFICACY AS A PREDICTOR OF GUN VIOLENCE IN
TORONTO

by

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Bachelor of Arts, Wilfrid Laurier University, 2020

THESIS

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Master of Arts in Criminology

Wilfrid Laurier University

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Abstract

There has been a 42% increase in gun violence in Canada since 2013, largely due to increases in Toronto (Statistics Canada, 2022a). To gain a better understanding of this phenomenon, this study evaluated collective efficacy as a predictor of gun violence. Seven correlates of collective efficacy were identified including, low economic status, ethnic diversity, mobility, family disruption, employment rate, low educational attainment, and youth percentage in a population. This study included data from the City of Toronto's Open Data Portal and the 2016 Canadian Census. The data were pulled from various datasets and then were reorganized into one file, which was then used to run a multiple regression analysis. This allowed for the assessment of the relationship between the multiple correlates of collective efficacy and gun violence. Ultimately, this research was able to provide evidence that collective efficacy is an accurate predictor of gun violence in Toronto's neighbourhoods. Low economic status, ethnic diversity, employment rate, and youth percentage in a population were significant predictors of gun violence, and family disruption was a marginally significant predictor of gun violence. The results of this study are important as they directly advance knowledge regarding predicting gun violence using collective efficacy, and do so in a solely Canadian context. The results of this research can assist policy makers and community outreach programs to better identify and inform their gun violence reduction strategies across Toronto.

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Chapter 1: Introduction

Gun violence is a growing problem in Canada, which has seen a 42% increase since 2013 (Statistics Canada, 2022a). In Canada, in 2016, there were 130 homicides committed using a handgun, the highest numbers since 2005 (Statistics Canada, 2022a). “These accounted for 21% of homicides overall, and 58% of shooting homicides” (Statistics Canada, 2022a). It is vital to understand where, why and how gun violence occurs (Johnson et al., 2021). A gun violence incident “is an incident of death, injury, or threat with firearms, regardless of intent. Gun violence casualties consist of injuries or deaths (homicide or suicide) due to firearm use” (Johnson et al., 2021, p. 1). This research will study gun violence from a uniquely Canadian perspective and will utilize collective efficacy as a predictor of gun violence (Sampson et al., 1997). As the national increase in gun violence since 2013 is largely due to more victims in Toronto, this research will focus specifically on gun violence in Toronto’s neighbourhoods (Statistics Canada, 2022a). To measure collective efficacy, the following correlates will be used: low economic status, ethnic diversity, mobility, family disruption, employment rate, low educational attainment, and youth percentage in a population. This research will be able to provide a deeper understanding of the gun violence epidemic in Toronto that will be extremely useful for gun violence reduction policies.

Chapter 2: Literature Review

Introduction

Gun violence is a growing problem in Canada, having increased by 42 percent since 2013, largely because of increases in Toronto (Statistics Canada, 2022a). There has also been a growing amount of concern regarding the use of firearms in homicides, despite Canada's relatively strict gun laws (Butters et al., 2011; Kamal & Burton, 2018; Lawson, 2012). This research explores the concept of collective efficacy and, using a quantitative approach, assesses how effective it is at predicting the gun violence rates in Toronto's neighbourhoods. A better understanding of how collective efficacy predicts gun violence could highlight factors that may contribute to gun violence and lead to a better understanding of how to combat them.

To date, much of the research on gun violence uses American data, where there are several dramatic differences between Canada and the United States regarding guns. (Beck et al., 2019; Hoskin, 2011; Lemieux, 2014, Statistics Canada, 2022a). This chapter first focuses on differences in gun culture, differences in the prevalence of guns as well as differences in the regulation of guns between the United States and Canada, and then explores how the concept of collective efficacy might help us understand gun violence in a Canadian context.

The purpose of this thesis is to study gun violence from a Canadian perspective, using Canadian data and to apply the concept of collective efficacy to achieve this. As collective efficacy originates in social disorganization theory and social cohesion, the shift from these theories to collective efficacy will be examined, as well as its major contributors as informed by the literature. Specifically, it will assess the ability of low economic status, ethnic diversity, mobility, family disruption, employment rate, low educational attainment, and youth percentage

in a population, individually and as a group, to accurately predict gun violence in the City of Toronto.

Gun Culture, Prevalence, and Regulation of Guns in the United States and Canada

A common theme throughout the literature on gun violence is that due to the dramatic political and cultural differences between Canada and the United States, research findings may not be generalizable across the two countries (Hoskin, 2011; Kamal & Burton, 2018; Lemieux, 2014; Yamane, 2017). This section specifically focuses on differences in gun culture, differences in the prevalence of guns, as well as differences in the regulation of guns between the two countries. Several studies suggest that the United States is an anomaly regarding their gun culture in relation to other developed countries such as Canada, Australia and many European countries (Kamal & Burton, 2018; Yamane, 2017). To understand these differences, it is crucial to examine how the concept of “gun culture” is used in the literature. Gun culture varies by country and thus has a slightly different meaning depending on the country. Generally, it encompasses the interactions of both individuals and institutions with firearms, as well as their thoughts, behaviours and laws surrounding guns (Boine et al., 2020).

Many studies point to the Second Amendment in the United States Constitution as a key element underpinning American gun culture (Kamal & Burton, 2018; Yamane, 2017). The Second Amendment of the United States Constitution reads as follows, “a well-regulated Militia, being necessary to the security of a free State, the right of the people to keep and bear Arms, shall not be infringed” (Wex, 2022, para. 1). Because of the specific wording of the second amendment, there has been considerable debate as to its intended scope (Wex, 2022). The two common schools of thought surrounding it are as follows: the individual rights theory which restricts legislative bodies from prohibiting firearm possession and the collective rights theory

which asserts that citizens do not have an individual right to possess guns and that all legislative bodies have the right to regulate firearms (Wex, 2022). Because both of these differing schools of thought are each regarded as correct by a large portion of Americans, this has led to a significant divide in their politics (Wex, 2022). The Democratic Party typically holds that the collective rights theory is the correct interpretation of the Second Amendment, while the Republican Party, as well as larger interest groups like the NRA subscribe to the individual rights theory and have therefore argued for the persistence of those rights. Yamane (2017) suggests that today's American gun culture is centered around self-defence, calling it the "culture of armed citizenship" (p. 5). Bellesiles (1996) states that the origins of American gun culture lies in their frontier heritage and it is assumed that "the nation's love affair with the gun is impervious to change, since its roots are so deep in our national history and psyche" (p. 426). This is very evident in the United States, as the "almost universal ownership of guns in the eighteenth century was enshrined in the Second Amendment to the Constitution" (Bellesiles, 1996, p. 426). It is also suggested that the gun culture in the United States grew with industrialization, because it wasn't until then that guns became a common commodity (Bellesiles, 1996; Rakove, 2002). The government relied on the firearms industry for capital development as well as support and enhancement of its markets (Bellesiles, 1996). This reliance continues to be evident as American gun culture features prominently in the media (Bellesiles, 1996). Bellesiles (1996) writes "the sincere love and affection with which our society views its weapons pours forth daily from the television and movie screens" (p. 426). Kamal and Burton (2018) suggest that this long history of gun culture being centered around self-defence may have contributed to the United States being "unique in its high rates of both gun ownership and homicides" (p. 320). Atlas (2019) suggests that while Canada has had their own frontier experience and history of guns, it does not

have a parallel gun culture. “While Americans glory in tales of the ‘Wild West’, Canadians proudly reply with their own narrative of a more civilized ‘Mild West’, part of a broader national image of Canada as the ‘Peaceable Kingdom’” (Atlas, 2019, p. 26). Some of the elements that may contribute to the United States’ gun culture may be the difference in the prevalence of guns as well as the regulation of guns, both of which will be examined below.

In examining the prevalence of guns in the United States, Hoskin (2011) argues that there are three main academic views on whether gun availability impacts gun violence. The first is that “the presence or absence of a firearm does not affect the probability that a crime will be committed”, the second is that “easy access to a gun raises the risk” and the third is that “the presence of a gun reduces criminal violence” (Hoskin, 2011, p. 126). It is generally accepted by scholars that only the second view is correct as the “best predictor of death by firearms is the possession of guns (gun ownership)” (Lemieux, 2014, p. 90). This view suggests that restrictive firearms regulation can save lives by enacting regulations such as imposing background checks, developing stricter conditions for access to firearms and banning specific weapons (Lemieux, 2014). Lemieux’s (2014) research found that “gun access predicts death by guns” and that this result “is trans-culturally consistent” as this finding was true in 25 advanced democracies and in all 50 states in the United States regardless of their cultural background (Lemieux, 2014, p. 90). Even within the United States, during the 10 years in which the Violent Crime Control and Law Enforcement Act of 1994 was in effect in the United States, total mass shootings, total victims and total injuries and fatalities were substantially lower than the 10-year periods directly preceding and succeeding the ban (Lemieux, 2014). The legacy of this law is complicated as although this act introduced unfavourable measures like expanding the death penalty, introduced the ‘three strikes and you’re out’ rules and provided billions in funding for prisons, it also

banned the manufacture of 19 military-style assault weapons, strengthened the federal licensing standards for firearms dealers and prohibited firearms sales and possession by those subject to family violence restraining orders (Eisen, 2019; National Criminal Justice Reference Service, 1994). As is demonstrated by this act's implications, reduced firepower capacity is clearly associated with fewer victims (Lemieux, 2014).

The difference in the regulation of guns between the United States and Canada relates mainly to Canada imposing strict background checks and implementing bans on owning certain weapons while the United States, generally does not. Although there are approximately 20,000 gun laws in the United States, most relevant laws are "generally lenient in nature and do not inhibit the widespread possession of handguns and assault weapons" (Kamal & Burton, 2018, p. 333). These differences have been attributed to the vastly different political climate and legislative structures in the United States and Canada (Kamal & Burton, 2018; Lemieux, 2014; Yamane, 2017). Kamal and Burton (2018) looked at various mass shootings in Canada and the United States and found that the ability of the Canadian government to enact stricter gun laws and policies following the occurrence of these mass shootings likely reduced the number of subsequent shootings. Additionally, they referenced powerful interest groups in the United States, such as the National Rifle Association (NRA), who successfully blocked the government's attempts to enact stricter gun laws and regulations (Kamal & Burton, 2018). Following the Columbine Shooting (1999) and the Sandy Hook Elementary School Shooting (2012) in the United States, as well as the Montreal Massacre (1989) and Concordia University Shooting (1992) in Canada, there was a public outcry in each country calling for stricter gun laws to be enacted at the federal level (Kamal & Burton, 2018). While the United States experienced policy gridlock, both times Canada was able to successfully enact stricter gun laws

following the aftermath of both incidents, namely Bill C-17 in 1991 and the Firearms Act of 1995 (Kamal & Burton, 2018). Most recently, another unimaginable tragedy occurred May 24th, 2022 in Uvalde, Texas, where nineteen children and two adults were killed in a shooting at an elementary school (The Texas Tribune, 2022). In response to the public outcry, on June 25th, 2022, President Joe Biden signed a bipartisan gun bill into law “intended to prevent dangerous people from accessing firearms and increase investments in the nation’s mental health system” (Cochrane & Kanno-Youngs, 2022, para. 2). While this has been hailed as the “strongest gun violence prevention law in the last 30 years”, the day prior to this, the Supreme Court ruled that New York state’s limits on carrying concealed handguns outside the home was unconstitutional (Jackson & Cowan, 2022, para. 9). This greatly illustrates the extent of the divide that exists in current American politics over the correct course of action regarding firearms.

To help explain the differences in each nation’s political climate and discuss why this policy gridlock occurs in the United States, Kamal and Burton (2018) turn to the idea of veto players. A veto player simply refers to those whose agreement is required for a legislative change (Kamal & Burton, 2018). They point to the fact that due to the institutional set up of the United States federal government (whereby there are three government branches), there are multiple access points which allow veto players (like the NRA) to influence the policy making process (Kamal & Burton, 2018). They argue that in Canada it is much easier to enact policy changes because while legislative “bills must pass through the Senate, the Senate cannot veto the bill, only attempt to modify it. Parties are the veto players in a parliamentary system, and when one party has a majority, it becomes the dominant player” (Kamal & Burton, 2018, p. 335). Additionally, Canada lacks powerful pro-gun lobby groups like the NRA which has heavily influenced firearms legislature in the United States (Kamal & Burton, 2018; Rakove, 2002).

While gun regulations can be passed/enforced by states as well as federal governments in the United States, Kamal and Burton (2018) state that “no significant policy change has been observed at the national level for twenty years” and that despite there being approximately 20,000 gun laws in the country, “most relevant laws are lenient and do not inhibit the widespread possession of handguns and assault weapons” (p. 333).

Given these major differences between Canada and the United States regarding their gun cultures, the prevalence of guns and their regulation of guns, the findings from gun research in one country are not generalizable in the other. Thus, this leaves a large knowledge gap on this subject in a Canadian context which this thesis research aims to fill by examining gun violence from a Canadian perspective.

Theoretical Basis

This research examines gun violence in Toronto using the concept of collective efficacy. In order to provide a thorough understanding of what collective efficacy is, it is important to first examine how the concept emerged from the social disorganization theory and social cohesion literature.

Social disorganization theory originates from Chicago School researchers Shaw and McKay in 1942 who studied the characteristics of an environment and the influences these characteristics may have on residents (Kawachi et al., 1999; Kubrin & Weitzer, 2003; Piscitelli & Doherty, 2018; Shaw & McKay, 1942; Steidley et al., 2017). They theorized that differing rates of delinquency could be attributed to differences in the physical and social environment across a geographic area (Shaw & McKay, 1942). Specifically, they focused on how “organized” neighbourhoods were and whether or not the level of organization correlated with crime and deviance (Kubrin & Weitzer, 2003). The term “social disorganization” is generally regarded as

the inability of a community to realize common goals or address social problems and disorders (Kawachi et al., 1999; Kubrin & Weitzer, 2003; Steidley et al., 2017). This inability to create social cohesion by residents in the community is believed to be caused by elements such as low economic status, ethnic diversity, high geographic mobility, and family disruption (Kawachi et al., 1999; Sampson & Groves, 1989; Shaw & McKay, 1942; Steidley et al., 2017). Shaw and McKay explain that these challenges lead to community breakdowns and also make it more difficult to instil moral values within their children (Kawachi et al., 1999; Piscitelli & Doherty, 2018; Shaw & McKay, 1942; Winterdyk, 2020). They believed that delinquency is a socially learned behaviour passed down from one generation of residents to the next and thus neighbourhoods experiencing social disorganization are more likely to face difficulty with instilling moral values and therefore foster delinquent values and unconventional behaviour in their youth (Kawachi et al., 1999; Piscitelli & Doherty, 2018; Shaw & McKay, 1942; Winterdyk, 2020).

By the 1980s, social disorganization theory's use had declined and it was criticized for a lack of empirical measurement of neighbourhood attitudes (Kubrin & Weitzer, 2003; Piscitelli & Doherty, 2018). It did however experience a revival in the 1990's through its use in the Project on Human Development in Chicago Neighbourhoods (PHDCN) which "gathered data on juvenile delinquency, adult crime, and substance abuse in Chicago" (Piscitelli & Doherty, 2018, p. 590). Although this research directly addressed the concerns about social disorganization theory at that time, it has faced new criticisms in recent years. These concerns are that social disorganization theory does not adequately explain the impact of formal social control mechanisms, it places an overemphasis on official records, especially when using empirical analysis, it does not provide enough of a comprehensive reason as to why crime occurs at

specific spaces within neighbourhoods, and it fails to incorporate other important variables such as neighbourhood culture, formal social controls, and the urban political economy (Kubrin & Weitzer, 2003; Piscitelli & Doherty, 2018).

As the limitations of social disorganization theory became more prevalent, the concept of social cohesion became more popular as it was seen as a possibly superior construct (Fonseca et al., 2018; Mekoa & Busari, 2018). Social cohesion has its roots in Emile Durkheim's work in which he defined social cohesion as a characteristic of society that shows the interdependence between individuals of that society and adds that there should be an absence of latent social conflict as well as the presence of strong social bonds (Durkheim, 1897; Fonseca et al., 2018). Durkheim's influence can be seen in more recent examinations of how the concept of social cohesion functions. For instance, today's understanding of social cohesion has been expanded upon and is generally examined at three levels of analysis (Mekoa & Busari, 2018; Stanley, 2003). While Durkheim initially studied cohesion at the level of the community/society, interest in cohesion at the level of the individual and the level of the institutions has also developed (Fonseca et al., 2018; Stanley, 2003). At each of the three levels (individual, community and institution) researchers focus on different aspects of social cohesion (Mekoa & Busari, 2018). Social cohesion at the level of the individual refers to their individual behaviour, face-to-face communication, and sense of belonging and focuses on the "motives of the individual to be part of the group" (Fonseca et al., 2018, p. 243), while cohesion at the level of the community refers to strong social bonds, trust, a social environment, common goals, moral behaviour and norms (Fonseca et al., 2018; Stanley, 2003). At the institutional level, factors like life satisfaction, high equity, trust, multiculturalism, suicide rates and voting rates all affect social cohesion (Fonseca et al., 2018; Mekoa & Busari, 2018).

The literature surrounding social cohesion shows that while these three levels are generally agreed upon by scholars, there is no universal definition of social cohesion (Fonseca et al., 2018; Meko & Busari, 2018). Fonseca et al. (2018) highlight these disparities by showing some of the various definitions of social cohesion. “It is best defined by the absence of conflict or crime (Durkheim, 1897), a characteristic of society (Europe, 2008), a desire for affiliation (Festinger et al., 1950), a group property (Lott & Lott, 1966), a degree of stability (Parsons, 2013), the strength of connections (Braaten, 1991), as a transient state/process (Jeannotte, 2003), and the same as good relationships or a national identity (Alaluf, 1999)” (Fonseca et al., 2018, p. 241). Despite the various definitions of social cohesion, it seems that currently, the most accepted definition of social cohesion includes the development of well-being, sense of belonging and voluntary social participation from the members of a society (Fonseca et al., 2018). In accordance with this, Stanley (2003) suggests that “social cohesion and liberal social values seem to exist in a sort of virtuous circle. . . if individuals can count on tolerance, respect for the rule of law and have confidence that their potential partners entertain a certain degree of respect for rights of others, they are more likely to cooperate with others” (p. 10).

While thus far social disorganization theory and social cohesion have been discussed as two different entities, the literature is clear that they are intertwined. Recent literature has moved away from using the terms social cohesion and social disorganization and has since favoured the use of the term collective efficacy (Steenbeek & Hipp, 2011; Wang et al., 2020). Sampson and Groves (1989) state that social organization and social disorganization are two ends of the same continuum “with respect to the systemic networks of community social control” (p.777) and so communities may have varying degrees of social cohesion. Seeing an analogy between individual efficacy and neighbourhood efficacy, Sampson et al. (1997) coined the term

“collective efficacy”. They determined that a combined measure of cohesion, mutual trust and expectations of intervention by others led to what they called collective efficacy, which they found was correlated with reduced violent crime rates (Sampson et al., 1997; Steenbeek & Hipp, 2011). Sampson et al. (1997) define collective efficacy as “social cohesion among neighbours combined with their willingness to intervene on behalf of the common good” (p. 918). Collective efficacy acts as an informal social control, which can help regulate the behaviours of those within the greater community (Sampson & Groves, 1989; Sampson et al., 1997; Steenbeek & Hipp, 2011; Wang et al., 2020). Wang et al. (2020) write that the association between risk factors and violence is “mediated by social cohesion and willingness to intervene in neighbourhood events – broadly conceived as the collective efficacy of a community – which is itself negatively impacted by community violence” (p. 2). Thus, this research will draw on the concept of collective efficacy and will examine the varying degrees of collective efficacy present in neighbourhoods. Collective efficacy should be able to accurately predict gun violence as many of its major elements have been shown to be related to elevated levels of gun violence.

Measuring Collective Efficacy

When measuring collective efficacy, scholars have drawn upon variables from both social disorganization theory and social cohesion, namely low economic status, ethnic diversity, mobility, family disruption, employment rate, low educational attainment, and youth percentage in a population (Fonseca et al., 2018; Sampson et al., 1997; Siegel et al., 2020; Wang et al., 2020). Low economic status, ethnic diversity, mobility, and family disruption have their roots in social disorganization theory (Kawachi et al., 1999; Sampson & Groves, 1989; Shaw & McKay, 1942; Steidley et al., 2017), and employment rate and low educational attainment are typically assessed in studies using social cohesion (Fonseca et al., 2018; Meko & Busari, 2018; Siegel et

al., 2020; Stanley, 2003). In an effort to link the concepts of social disorganization theory and social cohesion into the broader concept of collective efficacy, these six variables will be assessed, in addition to a seventh variable, youth percentage in a population, which draws from both social disorganization researchers Shaw and McKay as well as the concept of social cohesion (Mekoa & Busari, 2018; Shaw & McKay, 1942; Siegel et al., 2020; Winterdyk, 2020).

Low Economic Status

Economic status can be measured in two ways, using discrete categories, (i.e. membership in hierarchally ordered classes) or continuously (i.e., by earnings, income, etc.) (Bowles & Gintis, 2001). It typically refers to earnings, income, wealth and other measures of economic success (Bowles & Gintis, 2001). Sampson and Groves used low economic status in their research and suggest that “lower economic-status communities may have higher delinquency rates in part because police concentration is greater there compared with higher status areas. Further, the type of community in which police-citizen encounters occur may influence the actions taken by police” (1989, p. 776; Kawachi et al., 1999). They state that the probability of arrest across communities has been demonstrated to decline substantially with the increasing of socioeconomic status, and that this findings was independent from the type of crime committed as well as other correlates of arrest decisions (Sampson & Groves, 1989). Sampson and Groves (1989) also suggest that “low-socioeconomic-status communities will suffer from a weaker organizational base than higher-status communities” (p. 780) which leads to a further breakdown of social cohesion within those neighbourhoods (Kawachi et al., 1999; Oraka et al., 2019). In other words, because of this relationship, both crime reporting rates as well as actual gun violence rates may be higher in lower economic status communities/neighbourhoods.

Ethnic Diversity

Ethnic diversity refers to the presence of people from a variety of cultural and ethnic backgrounds or identities (Steenbeek & Hipp, 2011). Steenbeek and Hipp (2011) studied ethnic heterogeneity/diversity and found that it significantly affected social cohesion as higher levels of it led to more subsequent disorder within neighbourhoods. To explain why this occurs, it is believed that ethnic diversity amongst a community would impede communication between individuals and groups thus preventing shared norms and values to be established (Kubrin & Weitzer, 2003; Sampson & Groves, 1989; Steenbeek & Hipp, 2011). Several other research studies assessed the relationship between ethnic diversity and gun violence and found that higher levels of ethnic diversity were correlated with higher rates of gun violence (Johnson et al., 2021; Kubrin & Weitzer, 2003; Oraka et al., 2019). It is predicted that neighbourhoods with higher levels of ethnic diversity will have higher levels of gun violence.

Mobility

Mobility rates are defined as the number of individuals or households moving in and out of neighbourhoods in a given year (Steenbeek & Hipp, 2011). Like ethnic diversity, neighbourhoods with high mobility rates, and therefore higher instability, are believed to contain lower rates of collective efficacy (Sampson & Groves, 1989; Steenbeek & Hipp, 2011; Wang et al., 2020). Steenbeek and Hipp (2011) state that “residential instability impedes the formation and maintenance of stable relationships, which are necessary for social control” (p. 837). Additional studies have also used mobility rates as a measure of collective efficacy (Sampson & Groves, 1989; Wang et al., 2020). It is predicted that neighbourhoods with higher mobility rates will have higher instances of gun violence.

Family Disruption

Family disruption can be defined as events that disrupt the structure of the family and includes such events as divorce, separation, and parental death (Sampson & Groves, 1989). Several studies have used this when measuring collective efficacy (Campbell et al., 2019; Kawachi et al., 1999; Sampson & Groves, 1989). They argue that marital and family disruption lead to lower rates of collective efficacy within a community, as single parent households provide less supervision and guardianship to their children (Kawachi et al., 1999; Sampson & Groves, 1989). Therefore a community consisting of many single-parent households would lack collective efficacy and family control (Kawachi et al., 1999; Sampson & Groves, 1989). Thus, communities that contain higher instances of family disruption are predicted to have higher rates of gun violence.

Employment Rate

The employment rate refers to the share of the labour force that is employed (Clemens & Palacios, 2018). Statistics Canada provides a definition of this stating that the “number of employed persons expressed as a percentage of the population 15 years of age and over. The employment rate for a particular group (age, sex, marital status, province, etc.) is the number employed in that group expressed as a percentage of the population for that group” (Statistics Canada, 2015, para. 30). Several studies have used various employment rates when measuring collective efficacy (Feng & Hu, 2013; Kawachi et al., 1999; Siegel et al., 2019; Siegel et al., 2020; Wang et al., 2020). Campbell et al. (2019) included several structural factors known to be associated with gun violence, including unemployment rate. This is due to the fact that persistently low employment leads to labour force detachment and is a contributor to low

economic status (Kawachi et al., 1999). It is predicted that low employment rates or high unemployment rates are related to increased rates of gun violence.

Low Educational Attainment

Educational attainment “refers to the highest level of education that a person has successfully completed” (Statistics Canada, 2015, para. 26). Wang et al. (2020) assert that exposure to violence is associated with lower high school graduation rates and lower rates of college attendance and that this exposure negatively impacts the collective efficacy within a community/neighbourhood. This is due to the fact that neighbourhoods with a higher exposure to violence are believed to face difficulty instilling moral values and therefore are more likely to foster delinquent values and unconventional behaviour (Kawachi et al., 1999; Piscitelli & Doherty, 2018; Shaw & McKay, 1942; Winterdyk, 2020). As low educational attainment has been shown to contribute to a lack of collective efficacy in previous research regarding gun violence, it will also be used as a measure in this research (Johnson et al., 2021; Kawachi et al., 1999; Oraka et al., 2019; Ou et al., 2007; Wang et al., 2020). It is predicted that higher rates of gun violence occur in areas with lower educational attainment rates.

Youth Percentage in a Population

Youth are typically considered to be below the age of 25 (Circo et al., 2018). This age distinction typically reflects the age-crime curve in which deviant behaviour tends to occur (Circo et al., 2018). Neighbourhoods and communities experiencing low social cohesion are believed to face a more difficult time in instilling moral values within their children as delinquency is a socially learned behaviour passed down from one generation of residents to the next (Kawachi et al., 1999; Piscitelli & Doherty, 2018; Shaw & McKay, 1942; Winterdyk, 2020). Additionally, adolescents who typically are more impulsive and lack the capacity to

account for future consequences may be more likely to use a weapon (Rowan et al., 2019; Sampson & Groves, 1989). This violent offending by young offenders is often motivated by gang violence (who often lack positive role models) and thus “street-corner teenage peer groups” will have a significant effect on both crime and delinquency rates (Circo et al., 2018; Sampson & Groves, 1989). Several studies have included youth as a measure of collective efficacy and thus it will be utilized in this research as well (Campbell et al., 2019; Circo et al., 2018; Hsu et al., 2021; Kawachi et al., 1999). It is predicted that neighbourhoods with higher rates of youth would experience more occurrences of gun violence.

Literature Gap/Conclusion

Gun violence is a critical issue in Canada that requires more research to be able to understand how to address it. Because of vast differences between Canada and the United States in the gun culture, the prevalence of guns, and the regulation of guns, the findings may not be transferrable between the two (Atlas, 2019; Kamal & Burton, 2018; Yamane, 2017). Since much of the literature about gun violence and gun culture is focused on US statistics and regulations, there is a definitive knowledge gap with regards to gun violence in a Canadian context (Hoskin, 2011; Kamal & Burton, 2018). This research will use Canadian data to build on the findings in the literature by assessing the extent to which the correlates of collective efficacy within communities accurately predict the gun violence rates of that neighbourhood. This research hypothesizes that based on the existing literature, lower economic status, higher rates of ethnic diversity, higher rates of mobility, higher rates of family disruption, lower employment rates/higher unemployment rates, lower educational attainment, and an increased number of youth in a population will be associated with elevated rates of gun violence.

The data for the analysis will come from the City of Toronto's Open Data Portal as well as from the 2016 Canadian Census. Using this publicly available data to conduct the research allows for use of a larger set of data than is otherwise able to be gathered and will provide insight into whether variables related to collective efficacy can, both individually and as a group, predict gun violence. As Toronto is not only a major contributor to the overall gun violence rates in Canada, but is also diverse and contains varied neighbourhoods with differing levels of social supports, using Toronto-centered data will allow for more accurate conclusions regarding gun violence in Toronto, and perhaps more broadly, Canada as a whole.

Chapter 3: Methodology

Introduction

This chapter outlines the research methodology used to test the extent to which collective efficacy predicts gun violence in Toronto. Due to the dramatic differences in the gun culture, prevalence of guns and regulation of guns between the United States and Canada, there is a knowledge gap surrounding Canadian data on this topic. This chapter will also focus on the data sources used and discuss the variable creation process, focusing specifically on the seven measures: low economic status, ethnic diversity, mobility, family disruption, employment rate, low educational attainment, and youth percentage in a population. It will then discuss the analytic strategy for the data.

Data Sources

After careful consideration of the research question and a review of related literature, secondary data analysis was determined to be the best methodological approach. Secondary data is any data that the researcher did not collect themselves (Hillier, 2022). Typically, the data were generated by large governmental or health institutions as part of record keeping (Benedictine University, 2022). Secondary data analysis involves applying theories and conceptual skills to use existing data taken from one or more sources to answer a research question (Johnston, 2014). It is a flexible approach that can be used in several ways and is considered to be “an empirical exercise with procedural and evaluative steps, just as there are in collecting and evaluating primary data” (Johnston, 2014, p. 620). One main advantage to this process is that the data already exists and “can be evaluated for appropriateness and quality in advance of actual use” (Johnston, 2014, p. 622). In order to accurately use the data, the researcher must obtain all of the documentation from the primary data regarding processes and protocols, (i.e., questionnaire,

coding), as well as have access to the raw data in order to perform new analyses (Johnston, 2014; Stewart & Kamins, 1993). Oraka et al.'s (2019) research is an excellent example of secondary data use in research that is similar to the present study. In that study, the researchers used data from the US General Social Survey (GSS) to examine gun ownership and support for gun control measures across the United States. The current research, evaluates gun violence using collective efficacy, employs similar methods using secondary data from the Canadian Census that have been collected from various sources.

Once variables related to collective efficacy were chosen, searches were conducted for datasets using various open data portals including the City of Toronto's Open Data Portal (City of Toronto, 2022d), the Toronto Police Service Public Safety Data Portal (Analytics and Innovation, 2019), and publicly available datasets through Statistics Canada (Statistics Canada, 2022b). From these searches, the following datasets were identified as containing measures and data that would be appropriate for the current study: "Neighbourhood Crime Rates", "Neighbourhood Profiles" (as well as the "At A Glance" feature), and "Census of Population, 2016 [Canada]: Topic Based Tabulations [B2020]". Specific details on how the datasets were merged into one document as well as the steps taken to do so are described in Appendix B, and details regarding the variables that were used from each dataset are in Appendix A. The data were organized by neighbourhood, which refers to the City of Toronto's 140 social planning neighbourhoods (City of Toronto, 2022b). They were developed to help government and community organizations with local planning by providing "socio-economic data at a meaningful geographic level" (City of Toronto, 2022b, para 3). These neighbourhoods have stable boundaries and remain consistent over time, making them a viable organizer for this dataset (City of Toronto, 2022b). While this remains true, as the neighbourhood boundaries have

remained consistent since the late 1990s; as of April 22nd, 2022, 16 of the existing 140 neighbourhoods in Toronto were split and divided into 34 new ones creating a new total of 158 social planning neighbourhoods in Toronto (City of Toronto, 2022c). This occurred because of “differential population growth over the last 20 years” which has seen “large population increases in parts of the city while other neighbourhoods saw no growth” (City of Toronto, 2022c, para. 10). However, as the data used in this thesis project was collected from years prior to the creation of these new neighbourhoods, for the purposes of this project, Toronto will be considered to have a total number of 140 neighbourhoods.

Variable Creation

Gun Violence

Gun violence was used as a measure of shooting rates across Toronto’s neighbourhoods. This measure was created using data from the “Neighbourhood Crime Rates” dataset found in the City of Toronto’s Open Data Portal. All of the crime rates in this dataset were calculated using the crime count per 100,000 population, which is the standard definition used by Statistics Canada (City of Toronto, 2022a). This measure allows for comparisons of crime between geographic areas with populations of different sizes (City of Toronto, 2022a). While the actual shooting counts were also available through the “Neighbourhoods Crime Rates” dataset, the shooting rates were used because “crime rate provides a fairer comparison of the crime over time by taking into account the change in population in the region” (City of Toronto, 2022a, para. 2). As referenced in Appendix A, several columns of data were copied into the “Thesis Dataset” file, specifically, the shooting rates from 2014 to 2020. Using SPSS, the gun violence variable was created by averaging the shooting rates from 2016 to 2020. The variable, `ShootingAverage2016_20`, therefore represents the average shooting rate of each neighbourhood

across the 5 years from 2016 to 2020. This was done to examine the influence of the seven independent variables (which contain only data from 2016) on the gun violence in Toronto neighbourhoods in subsequent years (2016-2020). It is important to note that this gun violence measure does not include suicide rates due to the availability of the data.

Low Economic Status

Low economic status was assessed using a measure of low after-tax income. This measure, found in the “Neighbourhood Profiles At A Glance” feature from the City of Toronto’s website is called “PercentLIMAT”. “PercentLIMAT” is the percentage of people in private households who are living with income below the median after-tax household income in Canada (Social Policy, Analysis & Research, 2022). Several other studies have measured low income using income medians as a threshold, with those beneath this threshold being classified as “low income” (e.g., Johnson et al., 2021; Oraka et al., 2019; Siegel et al., 2020).

Ethnic Diversity

Ethnic diversity was measured using language data, a measure from the “At A Glance” feature of the “Neighbourhood Profiles” dataset. This dataset is from the City of Toronto’s Open Data Portal and includes data on the percentage of residents whose mother tongue is not English. “Mother tongue” is “the first language learned at home in childhood and still understood by the individual at the time of the census” (Social Policy, Analysis & Research, 2022, p. 9). Measuring ethnic diversity using mother tongue is an idea that originated with the Linguistic Diversity Index (LDI). The Linguistic Diversity Index is the “probability that any two people selected at random would have different mother tongues. Calculated using Greenberg’s Linguistic Diversity Index. . . lower values mean less diversity, higher values mean more diversity” (City of Toronto, 2011, p. 13). Unfortunately, because the LDI was only collected in

2011, the data was unusable for this model and thus additional language data was collected, specifically the mother tongue data. While using mother tongue data to measure ethnic diversity was conceived with the LDI, using other linguistic data to represent ethnicity is not a new concept. Michalopoulos (2012) discusses the origins of ethnolinguistic diversity and states that ethnic diversity is typically constructed using information on the location of linguistic groups.

Mobility

Mobility was assessed using migrant data from each neighbourhood across Toronto. This measure, which was created using data from the “Neighbourhood Profiles” dataset found on the City of Toronto’s Open Data Portal, was taken from a variable labelled “MigrantPercent”, which is the percentage of migrants within each neighbourhood. This was created by adding the total number of internal and external migrants and dividing it by the total number of census families in private households. Finally, this rate was turned into a percentage by multiplying by 100. Internal migrants “includes migrants who lived in Canada 1 or 5 years ago. This includes persons who moved to a different city, township, village, municipality or Indian reserve within Canada” (Statistics Canada, 2017b, para. 8). External migrants are defined as migrants who did not live in Canada 1 or 5 years ago” (Statistics Canada, 2017b, para. 9). Both migrant data across one year as well as five years was collected, but due to a large number of missing data in the five-year category, this data was unable to be used. Using migrants to represent mobility is a common practice in mobility studies (Kumar & Moledina, 2017). Kumar and Moledina (2017) state that mobility is an umbrella term that encompasses multiple ways of understanding movement, including the more narrow term migration. It is important to note that while mobility typically includes the movement of residents in and out of the neighbourhood,

this measure was only able to capture the mobility of residents into the neighbourhoods due to the data that was available.

Family Disruption

Family disruption was assessed using various indicators. This measure, found in the “Neighbourhood Profiles” dataset from the City of Toronto’s Open Data Portal, is made up of several types of disruptions to a family, including divorces, separations or the death of a spouse. While there was no specific definition provided for the terms “divorced”, “separated”, and “widowed”, based on the classification system that Statistics Canada used to collect the information, each of these would be a familial disruption (Statistics Canada, 2016). The 2016 census provided respondents with six options for marital status: (1) married, (2) living common law, (3) never married (not living common law), (4) separated (not living common law), (5) divorced (not living common law), (6) widowed (not living common law) (Statistics Canada, 2017a). Divorced, separated and widowed were added together to create a total of family disruption in each neighbourhood. This was then used to create a percentage of family disruption in each neighbourhood by dividing the family disruption total by the total number of census families in private households and then multiplying by 100. Other important indicators of family disruption that were left out of the measure because of a lack of data were parental deployment, veteran suicide, removal of children from the family home, and families that were created outside of marriage.

Employment Rate

Employment rate was measured using actual employment rates gathered from the “Neighbourhood Profiles” dataset through the City of Toronto’s Open Data Portal. This measure was defined as “people who: did paid work in an employee-employer relationship or self-

employment, or did unpaid work in the operation of a business owned by a family member of the same household, or had a job but were not at work due to illness or disability, personal or family responsibilities, vacation or labour dispute” (Social Policy, Analysis & Research, 2022, p. 18).

While some researchers have used unemployment rates as their measure, Clemens and Palacios (2018) argue that the unemployment rate is no longer a reliable gauge of labour market performance. They give the example of the change in employment and unemployment rates between 2008 and 2016 in Canada (Clemens & Palacios, 2018). Typically, one would expect the employment and unemployment rates to have an inverse relationship: as one rises, the other one declines (Clemens & Palacios, 2018). Between 2008 and 2016, the employment rate fell from 63.4 percent (2008) to 61.1 percent (2016). “At the same time, however, because of the falling labour market participation, the unemployment rate also fell – from 8.3 percent in 2009 to 7.0 percent in 2016” (Clemens & Palacios, 2018). They suggest that this change in labour force participation is largely due to the aging of Canadian society (Clemens & Palacios, 2018). Given these discrepancies, the employment rate was deemed to be more appropriate for use in this model.

Low Educational Attainment

Low educational attainment was measured using data from “Neighbourhood Profiles” from the City of Toronto’s Open Data Portal. In this model, low educational attainment was considered to be those who had not achieved a certificate, diploma or degree as well as those who had only completed high school, or an equivalency certificate. Oraka et al. (2019) included four levels of educational attainment in their study: less than high school graduate, high school graduate/GED, some college, and college graduate or more, and thus the bottom half was considered lower educational attainment (i.e., less than high school graduate and high school

graduate/GED). To create a measure of low educational attainment for the model, the total for those who had not achieved a certificate, diploma or degree was added to those who had completed high school or an equivalency certificate. This variable was then turned into a low educational attainment rate by dividing it by the total number of census families in private households and was then converted into a percentage by multiplying by 100.

Youth Percentage in a Population

Youth percentage in a population was assessed using data from the “Neighbourhood Profiles At A Glance” feature through the City of Toronto’s Open Data Portal. In this measure, “youth” were considered to be between the ages of 15 and 24, and thus this measure is a percentage of the population in each neighbourhood within this age range. Circo et al. (2018) parallel these ages and state that “while no single definition has been established as to what constitutes a ‘young’ or ‘youthful’ victim or offender, those below the age of 25 have generally been considered ‘youthful’ individuals by a number of criminological studies” (p. 801). They suggest that this age distinction reflects the “age-crime curve in which criminal and deviant behaviour tends to manifest during the late teen years, peaking during young adulthood, and decreasing gradually thereafter” (Circo et al., 2018, p. 801).

Analytic Strategy

Multiple regression is a statistical technique that allows for an assessment of the relationship between multiple independent variables and one dependent variable (Tabachnick & Fidell, 2013). This is an appropriate analysis to run as this research project examines how well a set of predictors related to collective efficacy predicts gun violence. There are three main types of multiple regression analyses: hierarchal, stepwise, and standard (Pallant, 2016; Plonsky & Ghanbar, 2018). In hierarchal multiple regression, the independent variables are added in a

specific order determined by the researcher (Pallant, 2016; Plonsky & Ghanbar, 2018). The sequence in which the independent variables are added to the model is based on their logical or theoretical importance (Plonsky & Ghanbar, 2018). As there were no assumptions or hypothesis in the literature surrounding the order in which each of the seven measures of collective efficacy should be added to a regression model, hierarchal multiple regression was not used in the current model. In stepwise multiple regression there is also an assumption that the order of the independent variables matters, but unlike hierarchal multiple regression, where the researcher uses logic to order the independent variables, in stepwise multiple regression the independent variables are assigned to the model one by one in an order determined by the statistical package based on statistical criteria (Plonsky & Ghanbar, 2018). Again, because the predictions in the current research were not based on a specific ordering of the independent variables, this method of regression was not used. Instead, a standard multiple regression was chosen because it best suited the data and the research question. Standard multiple regression is useful for explanatory purposes in which one wants to estimate the effect of several different independent variables on a dependent variable (Pallant, 2016; Plonsky & Ghanbar, 2018). It is also helpful when explaining how much unique variance in the dependent variable each of the independent variables explains (Pallant, 2016). This analysis technique will make it possible to determine how well the data fit the proposed model of collective efficacy and gun violence, and also the extent to which each individual variables contributes to the model.

Conclusion

This chapter focused on the research methodology used to assess how effective a group of variables related to collective efficacy is at predicting the gun violence rates of Toronto neighbourhoods. Several secondary data sources were used in this standard multiple regression

analysis to test the seven measures of collective efficacy (low economic status, ethnic diversity, mobility, family disruption, employment rate, low educational attainment, and youth percentage in a population). The specifics of how each variable was created to represent its correlate of collective efficacy was addressed in detail, as well as how the dependent variable, gun violence was created. The next chapter provides the results of the multiple regression analysis.

Chapter 4: Results

Introduction

This chapter outlines the results of the multiple regression analysis. It includes descriptive statistics for all of the variables. It also discusses the process and outcomes of the evaluation of the assumptions of multiple regression analyses, including outliers, normality, linearity, homoscedasticity and multicollinearity. This chapter also discusses the significance of the overall model and the relationship between each independent variable and the dependent variable (gun violence).

Descriptive Statistics

Table 1 contains various descriptive data regarding the variables used in this model. The mean (M) of each variable is the mean of said variable across 116 neighbourhoods in Toronto. With the exception of the gun violence variable, all variables represent a percentage within the total neighbourhood population. For example, the mean of low economic status ($M = 18.92$) means that, when averaged across neighbourhoods, 18.92% of the sample could be considered to have low economic status. The gun violence variable represents the number of shootings per 100,000 population. Table 1 shows the average number of shootings between 2016 to 2020, averaged across the neighbourhoods of Toronto, was 2.78 instances of gun violence per 100,000 population. At 6.13, Glenfield-Jane Heights had the highest average number of gun violence instances per 100,000 population between 2016 and 2020, while 8 neighbourhoods had an average of 0 instances. Some other interesting data points to note are that 13.93% of households were recent migrants to their neighbourhood and 48.93% of households would have experienced family disruption in the form of either a divorce, separation or death of a spouse (widowed). 58.9% of the population of Toronto over the age of 15 are employed and 35.42% have either not

achieved a certificate, diploma or degree or had completed high school/equivalency certificate and would be in the low educational attainment category. Lastly, to note, 44.33% of Toronto's population grew up speaking a language other than English and 12.10 % of the population is made up of youth between the ages of 15 and 24.

Table 1
Descriptive Statistics and Correlation for Study Variables

	<i>N</i>	<i>M</i>	<i>SD</i>	1	2	3	4	5	6	7	8
1. Gun Violence ^a	116	2.78	1.44	————							
2. Low Economic Status	116	18.92	7.71	.45**	————						
3. Mobility	116	13.93	6.11	-.02	.32**	————					
4. Family Disruption	116	48.93	9.31	.33**	.50**	.20*	————				
5. Employment Rate	116	58.9	6.06	-.43**	-.51**	.20*	-.20*	————			
6. Low Educational Attainment	116	35.42	7.85	.51**	.48**	-.37**	.30**	-.64**	————		
7. Ethnic Diversity	116	44.33	14.93	.43**	.55**	.16	.19*	-.69**	.58**	————	
8. Youth Percentage in a Population	116	12.10	2.05	.33**	.37**	-.05	-.04	-.68**	.51**	.47**	——

^a Gun violence is per 100,000 but all others are percentage of the population.

* Correlation is significant at the 0.05 level.

** Correlation is significant at the 0.01 level.

Assumption Testing

Before conducting the standard multiple regression, several screening measures related to multiple regression were tested. These included assessing the appropriateness of the sample size for generalizability, identifying and dealing with outliers, and evaluating the four

main assumptions of multiple regression: normality, linearity, homoscedasticity and multicollinearity.

Sample Size

Although there are 140 total neighbourhoods in Toronto, 20 of those contained missing data for more than one measure and thus were unable to be included in the analysis. This left 120 neighbourhoods with complete data. There were also four outliers (detailed below), resulting in a final sample size of 116. To ensure that a sample size is large enough to run a multiple regression analysis, Stevens (1996) suggests that approximately 15 participants per independent variable are needed for a reliable equation. Additionally, Tabachnick and Fidell (2013) provide an equation to calculate sample size requirements: $N > 50 + 8m$ (where m = the number of independent variables in the equation). In both of these cases the sample size ($N = 116$) was deemed large enough to power this type of analysis [$7 \times 15 = 105$; $50 + 8(7) = 106$].

Outliers

As multiple regression can be sensitive to outliers, this was the next check that was performed (Pallant, 2016). Typically, outliers are considered to be data points with standardized residual values above 3.3 or less than -3.3 (Pallant, 2016; Tabachnick & Fidell, 2013). When the dataset was created, it was visually screened for any obvious outliers, and none were noted at that time. When the standardized residual values were examined, two cases had standardized residuals falling outside the acceptable range and thus were removed from the model (case 10, with a standardized residual of 4.18, and 62, with a standardized residual of 4.35). Another way to identify outliers is by using the Mahalanobis distances that are created in the file when a multiple regression analysis is run (Pallant, 2016). Pallant (2016) states that the Mahalanobis distance is “the distance of a particular case from the centroid of the remaining

cases, where the centroid is the point created by the means of all the variables” and that “this analysis will pick up on any cases that have a strange pattern of scores across the . . . dependent variables” (p. 292). Using the critical chi-square value which uses the number of independent variables in a model as the degrees of freedom, one can identify the critical value and compare it with the Mahalanobis distances from the analysis (Pallant, 2016; Tabachnick & Fidell, 2013). Using this method, the critical value was determined to be 24.32, and two more outliers were identified (cases 78 and 79) as they were much larger than the critical value (27.47 and 33.84 respectively). These outliers were also removed, resulting in a total of four outliers that were removed and a final sample size of 116. Cases 10 and 62 were outliers regarding gun violence and cases 78 and 79 were identified as multivariate outliers that did not fit with the regression model.

Multiple Regression Assumptions

To test the normality, linearity and homoscedasticity of the data, the Normal Probability Plot (P-P) of Regression Standardized Residual and a scatterplot of the gun violence were reviewed. In the Normal Probability Plot (P-P) (Figure 1), the data largely followed the desired line (straight diagonal from bottom left to top right), which suggests that there were no major deviations from normality or linearity. The partial regression plots for each variable were also examined and found to be consistent with this.

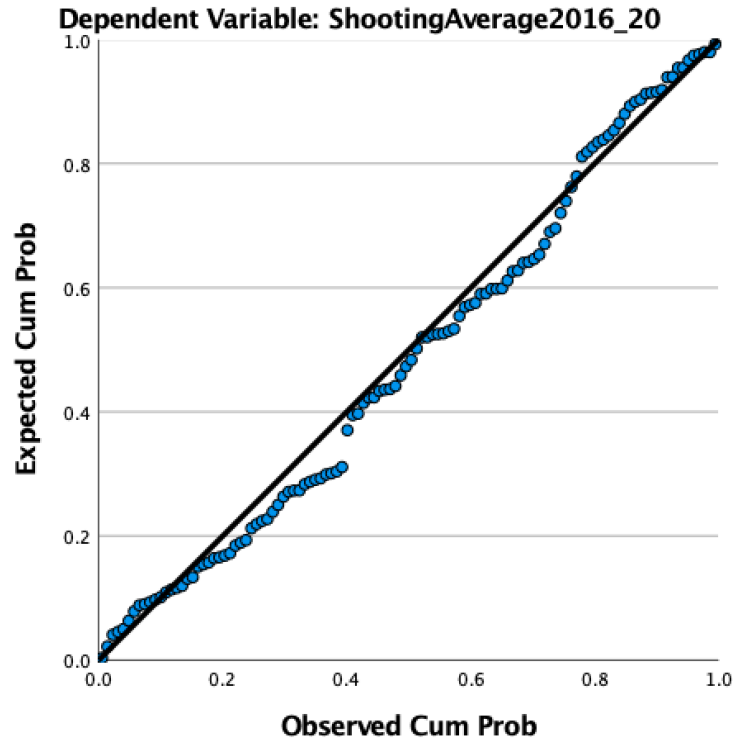


Figure 1: Normal P-P Plot of Regression Standardized Residual

The scatterplot of gun violence (Figure 2) was visibly examined and the data were found to be roughly rectangular, with the majority of the scores concentrated around the center (0,0) which reinforced the normality of the data. As no visible patterns in the data were found in either the Normality Probability Plot (P-P) or the scatterplot, it was determined that heteroscedasticity was not present in the data (Tabachnick & Fidell, 2013).

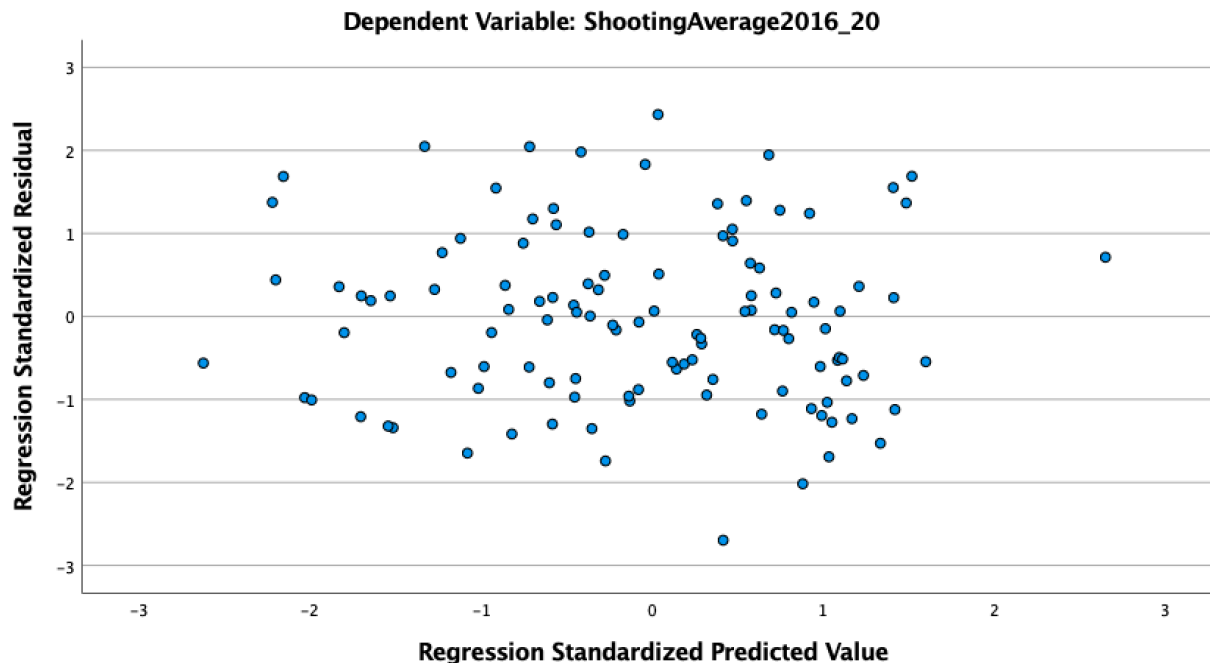


Figure 2: Gun Violence Scatterplot

To test for multicollinearity, the first step was to ensure that all the independent variables were related to some extent with the dependent variable. Pallant (2016) recommends a Pearson correlation coefficient of at least $r = 0.30$. To assess this, correlations between each independent variable and the dependent variable (gun violence) were calculated. Aside from mobility and family disruption which fell below 0.3 (-0.02 and 0.26 respectively), all of the independent variables were found to have a relationship with gun violence. The next step in assessing for multicollinearity is to ensure that the independent variables are not too closely related with each other, which could indicate that they are measuring the same construct. Ideally, the bivariate correlation should be less than $r = 0.70$ (Pallant, 2016). All of the correlations between the independent variables were below $r = 0.70$, with the two highest correlations occurring between employment rate and ethnic diversity ($r = -0.695$) and between employment rate and low educational attainment ($r = -0.670$) (see Table 1).

In addition, collinearity statistics were examined, specifically tolerance and variance inflation factor (VIF). “Tolerance is an indicator of how much of the variability of the specified independent is not explained by the other independent variables in the model” (Pallant, 2016, p. 159). The other value, VIF (variance inflation factor) is simply the inverse of the tolerance (1 divided by tolerance) (Pallant, 2016). In the model, both tolerance and VIF (shown in Table 2) were found to be consistent with the absence of multicollinearity. Tolerance statistics were above 0.1 (lowest score was employment rate = 0.253) and VIF was below 10 (highest score was also employment rate = 3.957). Thus it was determined that collinearity was not a concern with these data.

Finally, Cook’s distance “is used in regression analysis to find influential outliers in a set of predictor variables” and is a combination of “each observation’s leverage and residual values; the higher the leverage and residuals, the higher the Cook’s distance” (Glen, 2016, para. 1). A Cook’s distance greater than 1 suggests that a particular case may be influencing the results for the model as a whole. As the maximum Cook’s distance value in this model was 0.056, this indicated that there were no major issues with the data in this regard.

Gun Violence Regression Model

Model Summary

The seven independent variables (low economic status, ethnic diversity, mobility, family disruption, employment rate, low educational attainment, and youth percentage in a population) were entered into the regression model in order to determine to what extent they could predict the dependent variable (gun violence). The overall model was significant, $F(7, 108) = 8.107, p < .001$. The r-squared value of the model was 0.344 which indicates that, as a group, the independent variables accounted for 34.4% of the variance in gun violence.

Independent Variables

To assess whether each independent variable made a statistically significant unique contribution to the equation the standardized coefficients data was reviewed (Table 2). If the significant value is less than 0.05, the variable made a significant unique contribution to the prediction of the dependent variable (gun violence). Employment rate made the strongest unique contribution to explaining gun violence (standardized beta coefficient = 0.43, $p = 0.006$). Both low educational attainment and family disruption were not significant with $p = 0.346$ and $p = 0.079$ respectively. All of the other variables made statistically significant unique contributions towards the gun violence model and are shown below in Table 2.

Table 2
Gun Violence Coefficients

	Estimate	SE	95% CI		p	Collinearity Statistics	
			LL	UL		Tolerance	VIF
Low Economic Status	.316	.021	.014	.098	.010	.421	2.377
Mobility	-.246	.029	-.117	.000	.050	.392	2.552
Family Disruption	.170	.015	-.003	.055	.079	.661	1.512
Employment Rate	.433	.034	.027	.160	.006	.253	3.957
Low Educational Attainment	.129	.024	-.025	.070	.346	.326	3.070
Ethnic Diversity	.369	.012	.010	.059	.007	.342	2.925
Youth Percentage in a Population	.256	.078	.024	.334	.024	.489	2.047

Results with Outliers Included

As noted in the assessment of outliers above, four outliers were identified (cases 10, 62, 78 and 79) and were removed. Although this conforms to standard practice when performing assumption testing, the analysis was rerun with these outliers included to determine whether this

changed the findings in any meaningful way. With these cases included, the model was still significant, $F(7,112) = 5.064$, $p < 0.001$, and had an r^2 of 0.24. None of the independent variables changed with respect to whether they significantly predicted (or did not predict) gun violence (see Table 3 for a comparison of the findings with and without these outliers). Thus, removing the outliers resulted in a slightly improved model, but it did not change the overall results.

Table 3
Gun Violence Coefficients With and Without Outliers

	Excluding Outliers					Including Outliers				
	Estimate	SE	95% CI		p	Estimate	SE	95% CI		p
			LL	UL				LL	UL	
Low Economic Status	.316	.021	.014	.098	.010	.330	.025	.015	.114	.011
Mobility	-.246	.029	-.117	.000	.050	-.414	.032	-.155	-.028	.005
Family Disruption	.170	.015	-.003	.055	.079	.123	.017	-.014	.055	.248
Employment Rate	.433	.034	.027	.160	.006	.393	.040	.015	.175	.020
Low Educational Attainment	.129	.024	-.025	.070	.346	.042	.028	-.048	.064	.772
Ethnic Diversity	.369	.012	.010	.059	.007	.312	.015	.003	.061	.029
Youth Percentage in a Population	.256	.078	.024	.334	.024	.258	.086	.016	.357	.033

Conclusion

This chapter presented descriptive statistics of the variables included in the gun violence model, assessed the various assumptions regarding multiple regression analyses, including sample size, outliers, normality, linearity, homoscedasticity and multicollinearity, and provided the results of the main regression analysis. The overall analysis was significant and five out of seven independent variables provided a statistically significant unique contribution to the prediction of gun violence. As shown in Table 2, these were low economic status, mobility,

employment rate, ethnic diversity and youth percentage in a population. The two variables that did not significantly contribute to the model were family disruption and low educational attainment, although at $p = 0.079$, family disruption could be considered to be a marginally significant predictor. The multiple regression analysis was also run with the outliers included, to demonstrate that by removing them in the final analysis, no major changes occurred.

Chapter 5: Discussion

Introduction

This chapter outlines the key findings and contributions of this research project. It includes the specific findings regarding the overall model fit and each of the seven independent variables that made up the analysis and then reinforces the importance of Canadian-centered research surrounding gun violence. Finally, it discusses the limitations of this research and proposes recommendations and directions for future research regarding gun violence.

Key Findings and Contributions

This research set out to determine whether collective efficacy predicts the gun violence rates of Toronto's neighbourhoods. A standard multiple regression analysis was conducted with the data, with gun violence as the dependent variable and the following seven measures as independent variables: low economic status, ethnic diversity, mobility, family disruption, employment rate, low educational attainment, and youth percentage in a population. The overall model was significant and accounted for approximately 34% of the variance in gun violence. Five out of seven of the independent variables were significant in the model. In other words, collective efficacy was found to successfully predict gun violence rates in Toronto's neighbourhoods. This means that each of the correlates of collective efficacy that were found to be significant in the model are correlated with higher rates of gun violence. The exception to this is mobility, as higher rates of mobility resulted in lower rates of gun violence, the opposite of the prediction. Why it occurred will be discussed in further detail below. From a practical perspective, gaining a better understanding how each of these measures contributes to gun violence, as well as how they all interact with each other, is vital to shaping policy planning intending to reduce gun violence in Toronto's neighbourhoods.

Specific Findings

Low Economic Status

In the model, low economic status was found to significantly contribute to the level of gun violence in Toronto's neighbourhoods. This finding is consistent with the literature as economic status has been found to be a predictor of gun violence (Johnson, 2021; Kawachi et al., 1999; Oraka et al., 2019; Ou et al., 2007; Sampson & Groves, 1989; Steenbeek & Hipp, 2011; Wang et al., 2020). The literature has established that a greater police presence is typically concentrated in lower economic status communities, which therefore impacts the rate of police-citizen encounters and the crime reporting of that community (Kawachi et al., 1999; Sampson & Groves, 1989). Because of this relationship, crime reporting rates as well as gun violence rates may be elevated in lower economic status neighbourhoods (Kawachi et al., 1999; Sampson & Groves, 1989). In addition, these lower economic status communities are significantly correlated with weaker organizational bases, which leads to further breakdowns in social cohesion. Given that this is the case for lower economic status neighbourhoods, it makes sense that this measure was significant in the model.

Ethnic Diversity

Ethnic diversity was found to have made a statistically significant contribution to the gun violence model. This finding is consistent with the literature as ethnic heterogeneity or diversity has been shown to lead to lowered levels of social cohesion (Steenbeek & Hipp, 2011). Several studies have used ethnic diversity as a measure of collective efficacy, including Johnson et al. (2021), Kubrin and Weitzer (2003), and Steenbeek and Hipp (2011). Ethnic diversity in this model remains consistent with the literature regarding it.

Mobility

In the overall model, mobility was found to be significant, but in the opposite direction than was predicted. Contrary to predictions, higher rates of mobility were associated with lower rates of gun violence. One reason for this may be the limited data that were available. As discussed previously this measure of mobility only included those moving into the neighbourhood and not out of. In social disorganization theory, Shaw and McKay theorized that the number of people leaving the neighbourhoods was important, as it indicated that the residents viewed their home as temporary and therefore would not be invested in that community (Shaw & McKay, 1942; Winterdyk, 2020). Only measuring mobility into a neighbourhood rather than out of it may have inadvertently shown the opposite effect. Higher numbers of residents moving into a neighbourhood might, in fact, be indicative of greater collective efficacy.

Another reason why higher mobility into a neighbourhood is associated with lower gun violence might be that high inflows indicate wealth (which also negatively predicts gun violence), as those people are able to move and buy homes. This is unlikely for this model though, as mobility is positively correlated with low economic status (0.32), as seen in Table 1. Another reason could be that neighbourhoods with high inflows of migrants may be more homogenous because they are migrating into communities/neighbourhoods that they feel comfortable in or that have similar people to them. This hypothesis likely also isn't true for this model as mobility and ethnic diversity are poorly correlated with each other (0.16). More research on this is needed, and a better test of the model would include a measure of mobility that assesses movement in and out of the neighbourhood.

Family Disruption

In this model, family disruption was found to be marginally significant ($p =$

0.079). Several studies have used family disruption in their research (Campbell et al., 2019; Kawachi et al., 1999; Sampson & Groves, 1989). It has been proposed in the literature that family disruption is associated with lowered rates of collective efficacy because this type of disruption is detrimental to the family, resulting in single parents providing less supervision and guardianship to their children (Kawachi et al., 1999; Sampson & Groves, 1989). Although the relationship between family disruption and gun violence was in the predicted direction, it was only marginally significant in the gun violence model. This could be due to a variety of factors. Perhaps the measure that was used in the model could have been improved with additional data. Other family disruption data that may be important to provide a more thorough understanding of family disruptions could include parental deployment, veteran suicide, children being removed from the home and families that were created outside of marriage (Stanick et al., 2017). Unfortunately these data were not available and therefore were unable to be added to the measure.

Employment Rate

Employment rate was found to have made the strongest unique contribution to this model. This is consistent with the literature as even though many studies used unemployment rates in their research, as the employment rate falls or the unemployment rate rises, lower rates of collective efficacy are expected (Campbell et al., 2019; Feng & Hu, 2013; Kawachi et al., 1999; Siegel et al., 2020; Wang et al., 2020). Kawachi et al. (1999) linked “concentration effects” of living in lower economic communities with the lack of role models of labour force attachment, caused by persistently high unemployment. This is evident in the model as low economic status and employment rates are negatively correlated with each other (as shown in Table 1, $r = -0.51$). This means that as the employment rate increases, low economic

status decreases. As low employment leads to labour force detachment and is associated with lower levels of collective efficacy and therefore higher rates of gun violence, employment rate in this model remains consistent with the literature.

Low Educational Attainment

Low educational attainment was not significant in the gun violence model ($p = 0.346$). This finding is inconsistent with the literature, which has found that lower rates of educational attainment are associated with increased exposure to violence (Wang et al., 2020). This may be due, at least in part, to validity issues with the measure. In creating the low educational attainment variable for this model, both non-high school graduates and high school graduates were included in the total. After looking more closely at different studies, the literature appears split on whether a high school graduate or an equivalency certificate should be considered low or high educational attainment. Oraka et al. (2019) simply measured educational attainment using four levels and did not explicitly state what “low educational attainment” should encompass. Kawachi et al. (1999) included high school graduates in their “higher educational attainment” group. In order to determine whether including high school graduates in the variable for low educational attainment affected the outcome, the model was re-run with only those who did not finish high school. The results did not change significantly, as low educational attainment was still not significant (it changed from $p = 0.346$ to $p = 0.204$). Another thing to mention is that although there was no evidence of multicollinearity, the high correlation between low educational attainment and employment rate ($r = -0.670$) may be impacting the significance of the low educational attainment variable. As previously discussed, the typical cut-off for bivariate correlation should be less than $r = 0.70$ to ensure there is no multicollinearity (Pallant, 2016; Tabachnick & Fidell, 2013). While the correlation between low educational

attainment and employment rate falls within this cut-off, it is high and thus, employment rate may be inflating the size of error terms making it appear that the low educational attainment variable is not significant, even if it in fact is. Ultimately, more research is needed to determine whether this variable does not fit with the model, whether the measure that was used in the model was not representative of family disruption, was actually measuring something else, or could have been measured more accurately with different data that were not accessible.

Youth Percentage in a Population

The percentage of youth in a population was found to be significant in this model predicting gun violence. This was consistent with the literature, as it is believed to be more difficult to instill moral values within youth in neighbourhoods and communities experiencing low social cohesion (Kawachi et al., 1999; Piscitelli & Doherty, 2018; Shaw & McKay, 1942; Winterdyk, 2020). This, combined with the fact that youth tend to be more impulsive and thus are more unlikely to account for future consequences are therefore subsequently more likely to use a weapon (Rowan et al., 2019; Sampson & Groves, 1989). Thus, this finding supports the prediction that neighbourhoods with higher rates of youth would experience increased gun violence rates.

Limitations

Although this study was able to successfully measure many of the structural factors that contribute to collective efficacy, due to the nature of the data that was available, it was unable to measure some of the community factors. These factors include things like the level of trust neighbourhood residents have in each other, their trust in authorities, and their understanding of what community is, among other things. As these are more personal to the neighbourhood residents, the preferred method to collect this data would likely be to conduct qualitative in-depth

interviews (Murray, 2003). Murray (2003) suggests that the connection, rapport and trust in the researcher-participant relationship is important when engaging the participants in discussion. This method could have yielded rich, informative data regarding these community factors from residents, leading to a more thorough assessment of collective efficacy. Adding this qualitative strategy to the quantitative strategy that was used in this project would have been ideal, as a mixed methods approach allows for a richer, more multifaceted understanding of the topic of research (Yardley & Bishop, 2015).

Another limitation of this research is that it relied entirely on secondary data. While this collection strategy also yields certain benefits and was the best choice for this particular research question, it can pose challenges with respect to variable creation. One of the main limitations of secondary data is that because the data were collected for some other purpose, specific information that the researcher may like to have, may not have been collected, or does not fit their specific criteria (for example, different geographic region, data is outside of their year range, does not focus on their specific population of interest) (Johnston, 2014). Therefore, as was the case in this study, the researcher may have to choose less desirable data to use as a measure, as the more desirable data for that measure is unavailable (Johnston, 2014). As discussed above, for some of the variables, namely mobility, family disruption and low educational attainment, the measure may not have been able to fully capture the variable due to unavailability of the data. Additionally, in this research study, there was a lot of time and effort devoted to simply compiling and putting together the data files into one cohesive file (see Appendix B for the complete process). It was also difficult to easily figure out what each variable was measuring. This was ultimately remedied by continually referring back to the source definitions and

referencing guides. Both of these processes were time-consuming and somewhat inefficient, albeit necessary.

One final limitation of this research is that it only used data from Toronto, which while diverse and a good choice for this research, is not necessarily representative of the entire country. Thus, caution should be taken when generalizing these findings to the rest of Canada.

Recommendations and Directions for Future Research

As literature focusing on gun violence in Canada is limited, additional research should focus on expanding our understanding of it. As one of the limitations in this study was that it was unable to examine the impact that community factors of collective efficacy may have on gun violence, future research should aim to fill this gap. A mixed-methods research approach would be able to study both the structural and community level factors of collective efficacy and their impact on gun violence. Focusing future research on applying the findings from this research would be ideal and would ultimately help in reducing the gun violence rates in Toronto's neighbourhoods. While this research confirmed that low economic status, ethnic diversity, employment rate, and youth percentage in a population and likely family disruption are significant predictors of gun violence rates, understanding how each of these measures of collective efficacy directly affect gun violence rates among the various neighbourhoods in Toronto is essential in informing gun violence reduction strategies. Additionally, more research is needed regarding the other variables used in the model.

Practical Implications

The results of this study are important as they directly advance knowledge regarding predicting gun violence using collective efficacy, and do so in a solely Canadian context. This research is able to confirm that collective efficacy is an accurate predictor of gun violence in

Toronto neighbourhoods. It used the following seven measures of collective efficacy to do so: low economic status, ethnic diversity, mobility, family disruption, employment rate, low educational attainment, and youth percentage in a population. The practical implications of this finding are significant as policy makers and community outreach programs can utilize this information to better inform their gun violence reduction strategies across Toronto. For example by knowing that high employment rates are associated with lower rates of gun violence, policies and/or community outreach programs could focus on job creation as well as assisting those in gaining employment to help reduce the gun violence in certain communities and neighbourhoods. Another example could be that by knowing that higher percentages of youth in a population are associated with higher rates of gun violence, local community programs targeted specifically towards youth (like before- and after-school programs and Big Brother and Big Sister programs) may help deter youth from violence. Similarly, adding local community supports for disrupted families (like parenting groups and family counsellors) may help to lower gun violence rates in those communities/neighbourhoods.

Conclusion

Although there is a diverse literature that examines American gun culture, there is a definitive need for studies focusing solely on the Canadian context. Even though the United States and Canada share many similarities, the differences between their gun cultures, prevalence of guns, and their regulation of guns are so extreme that results and findings using American data are not generalizable to Canada. As gun violence remains a growing problem in Canada (Statistics Canada, 2022a), it becomes increasingly clear that understanding how to mitigate it is imperative to reducing it.

Appendix A

Data Sources and Organization

Census Data				
City of Toronto – Open Data Portal				Statistics Canada
Variables	Neighbourhood Crime Rates	Neighbourhood Profiles	Neighbourhood Profiles “At A Glance”	Census of Population, 2016 [Canada]: Topic Based Tabulations [B2020]
Gun Violence	Column CS – Shooting_Rate2014 Column CT – Shooting_Rate2015 Column CU – Shooting_Rate2016 Column CV – Shooting_Rate2017 Column CW – Shooting_Rate2018 Column CX – Shooting_Rate2019 Column CY – Shooting_Rate2020			
Low Economic Status		@_id 1039 – Under \$5000 @_id 1040 - \$5000 to \$9,999 @_id 1041 - \$10,000 to \$14,999 @_id 1022 - \$15,000 to \$19,999 @_id 1042 - \$20,000 to \$24,999 @_id 1043 - \$25,000 to \$29,999 @_id 1044 - \$30,000 to \$34,999 @_id 1045 - \$35,000 to \$39,999 @_id 1046 - \$40,000 to \$44,999	Low Income (LIM-AT) (percentage) Low Income (LICO-AT) (percentage)	

		<p>@_id 1047 - \$45,000 to \$49,999</p> <p>@_id 1048 - \$50,000 to \$59,999</p> <p>@_id 1049 - \$60,000 to \$69,999</p> <p>@_id 1050 - \$70,000 to \$79,999</p> <p>@_id 1051 - \$80,000 to \$89,999</p> <p>@_id 1052 - \$90,000 to \$99,999</p> <p>@_id 1053 - \$100,000 and over</p> <p>@_id 1054 - \$200,000 and over</p>		
Mobility		<p>@_id 91 - Total number of census families in private households</p> <p>@_id 2370 – Migrants (1 year)</p> <p>@_id 2371 – Internal Migrants (1 year)</p> <p>@_id 2372 – Intraprovincial Migrants (1 year)</p> <p>@_id 2373 – Interprovincial Migrants (1 year)</p> <p>@_id 2374 – External Migrants (1 year)</p> <p>@_id 2379 – Migrants (5 years)</p> <p>@_id 2380 – Internal Migrants (5 years)</p> <p>@_id 2381 – Intraprovincial Migrants (5 years)</p> <p>@_id 2382 – Interprovincial Migrants (5 years)</p> <p>@_id 2383 – External Migrants (5 years)</p>		
Family Disruption		@_id 103 – Lone Parent Census Families in Private Households		

		@_id 82 – Marital Status: Separated @_id 83 – Marital Status: Divorced @_id 84 - Marital Status: Widowed		
Employment Rate		@_id 1890 – Employment Rate		
Low Educational Attainment		@_id 1703 – Total: Highest Certificate, Diploma or Degree for the Population aged 15 years and over in Private Households @_id 1704 – No Certificate, Diploma or Degree @_id 1705 – Secondary (High) School Diploma or Equivalency Certificate		
Ethnic Diversity			Mother Tongue Not English (percentage)	Language data (census tracts)
Youth Percentage in a Population			Youth Age 15-24 (percentage)	

Appendix B

Data Manipulation

“Neighbourhood” and “Neighbourhood ID” became the first two columns (A and B) in a new excel file named “Thesis Dataset” (TD) where the data was transposed onto. The data (TD) was organized by the “Neighbourhood ID” beginning at 1 and increasing to 140, because it would provide the most ease and clarity when navigating the data.

The “Neighbourhood Crime Rates” dataset was organized by the arbitrary “object ID”, and so, the data needed to be copied and re-entered into the “Thesis Dataset” (TD) in the “Neighbourhood ID” order (as shown in Appendix 1). These cells were then formatted in excel “scientific” – “raise decimal places to 8”, in order to see all of the decimals. The layout of the “Neighbourhood Profiles” dataset was flipped on the x and y axis, and so the appropriate rows were copied and pasted into TD and then transposed. As the neighbourhoods in this dataset were organized alphabetically, the data also needed to be re-entered and organized instead by “Neighbourhood ID”. This occurred in one step and is also shown in Appendix 1. Using the “At A Glance” feature of the “Neighbourhood Profiles” dataset on the City of Toronto’s website, additional data was gathered and included at the end of the already converted “Thesis Dataset” SPSS file (noted in Appendix 1). In order to gain access to the final dataset “Census of Population, 2016 [Canada]: Topic Based Tabulations [B2020]”, the “Beyond 20/20” software was downloaded. As the files were divided by topic and census geographic division, language data, organized by census tracts (CTs) was chosen. The data was then copied and pasted from the “Beyond 20/20” software into a new excel file titled “Language 2016 Census”. As the “Beyond 20/20” software was only able to be downloaded and ran on a windows computer, this extra step was necessary for the researcher to access the data using a MacBook. From there, another new

excel file was created in order to convert Toronto's 535 census tracts into the 140 neighbourhoods that were used to organize the rest of the data. This excel file was titled "CT to neighbourhoods". In order to successfully convert the data, a number of sources were used including: eight census tract reference maps from the City of Toronto's website, an image labelling all 140 neighbourhoods, and an interactive mapping tool on the Toronto Police Service website that overlaid the neighbourhood boundaries on a map of Toronto with streets, rivers, and train tracks all visible underneath. From here, all of three materials were used to piece together which census tracts fit within each neighbourhood's boundaries, all of which was noted in the "CT to neighbourhoods" excel file. The language data was then collapsed into 29 significant linguistic categories and was added to the "Thesis Dataset" SPSS file (shown in Appendix 1).

References

- Analytics and Innovation. (2019). *Public Safety Data Portal*. Toronto Police Service.
<https://data.torontopolice.on.ca/>.
- Alaluf, M. (1999). Séminaire: Evolutions démographiques et rôle de la protection sociale: le concept de cohésion sociale.
- Atlas, P. M. (2019). Of Peaceable kingdoms and lawless frontiers: Exploring the relationship between history, mythology and gun culture in the North American west. *American Review of Canadian Studies*, 49(1): 25 – 49.
<https://doi.org/10.1080/02722011.2019.1573843>.
- Beck, B., Zusevics, K., & Dorsey, E. (2019). Why urban teens turn to guns: Urban teens' own words on gun violence. *Public Health*, 177: 66-70.
<https://doi.org/10.1016/j.puhe.2019.06.020>.
- Bellesiles, M. A. (1996). The origins of gun culture in the United States, 1760 – 1865. *Journal of American History*, 83(2): 425 – 455. doi: 10.2307/2944942.
- Benedictine University. (2022, April 22). *Public Health Research Guide: Primary and Secondary Data Definitions*.
<https://researchguides.ben.edu/c.php?g=282050&p=4036581>.
- Boine, C., Siegel, M., Ross, C., Fleegler, E. W., & Alcorn, T. (2020). What is gun culture? Cultural variations and trends across the United States. *Humanities and Social Sciences Communications*, 7(21): 1-12. <https://doi.org/10.1057/s41599-020-0520-6>.
- Bowles, S., & Gintis, H. (2001). The inheritance of economic status: Education, class and genetics. *International Encyclopedia of the Social and Behavioural Sciences: Genetics, Behaviour and Society*, 6(4): 132-141.

- Braaten, L.J. (1991). Group cohesion: A new multidimensional model. *Group, 15*: 39-55.
- Butters, J. E., Sheptycki, J., Brochu, S., & Erickson, P. G. (2011). Guns and sublethal violence: A comparative study of at-risk youth in two Canadian cities. *International Criminal Justice Review, 21*(4): 402-426. doi: 10.1177/1057567711428963.
- Campbell, J.K., Rothman, E.F., Shareef, F., & Siegel, M.B. (2019). The relative risk of intimate partner and other homicide victimization by state-level gender inequity in the United States, 2000-2017. *Violence and Gender, 6*(4): 211-218. doi: 10.1089/vio.2019.0023.
- Circo, G.M., Pizarro, J.M., & McGarrell, E.F. (2018). Adult and youth involvement in gun-related crime: Implications for gun violence prevention interventions. *Criminal Justice Policy Review, 29*(8): 799-822. doi: 10.1177/0887403416655431.
- City of Toronto. (2011, October 25). *2011 Census: Language*. Backgrounder.
- City of Toronto. (2022a). *About Neighbourhood Crime Rates*. Open Data Portal.
<https://open.toronto.ca/dataset/neighbourhood-crime-rates/>.
- City of Toronto. (2022b). *About Neighbourhood Profiles*. Open Data Portal.
<https://open.toronto.ca/dataset/neighbourhood-profiles/>.
- City of Toronto. (2022c). *About Toronto Neighbourhoods*. <https://www.toronto.ca/city-government/data-research-maps/neighbourhoods-communities/neighbourhood-profiles/about-toronto-neighbourhoods/>.
- City of Toronto. (2022d). *Open Data*. <https://open.toronto.ca/>.
- Clemens, J., & Palacios, M. (2018). *Why the unemployment rate is no longer a reliable gauge of labour market performance*. Fraser Institute. fraserinstitute.org.
- Cochrane, E., & Kanno-Youngs, Z. (2022). *Biden Signs Gun Bill Into Law, Ending Years of*

- Stalemate*. The New York Times. Retrieved July 2, 2022 from <https://www.nytimes.com/2022/06/25/us/politics/gun-control-bill-biden.html>.
- Council of Europe. (2008). Report of High-Level Task Force on Social Cohesion: Towards an Active, Fair and Socially Cohesive Europe.
- Durkheim, E. (1897/1951). *Suicide: A study in sociology*. New York: The Free Press.
- Eisen, L.-B. (2019, September 9). *The 1994 Crime Bill and Beyond: How Federal Funding Shapes the Criminal Justice System*. Brennan Center. <https://www.brennancenter.org/our-work/analysis-opinion/1994-crime-bill-and-beyond-how-federal-funding-shapes-criminal-justice>.
- Feng, S., & Hu, Y. (2013). Misclassification errors and the underestimation of the US unemployment rate. *American Economic Review*, 103(2): 1054-1070. <http://dx.doi.org/10.1257/aer.103.2.1054>.
- Festinger, L., Back, K.W., & Schachter, S. (1950). *Social Pressures in Informal Groups: A Study of Human Factors in Housing*. Lincoln: Stanford University Press.
- Fonseca, X., Lukosch, S., & Brazier, F. (2018). Social cohesion revisited: A new definition and how to characterize it. *The European Journal of Social Science Research*, 32(2): 231-253. doi: 10.1080/13511610.2018.1497480.
- Glen, S. (2016, July 13). *What is Cook's Distance?* Statistics How To. <https://www.statisticshowto.com/cooks-distance/>.
- Hillier, W. (2022, May 24). *What is Secondary Data? A Complete Guide*. Career Foundry. <https://careerfoundry.com/en/blog/data-analytics/what-is-secondary-data/>.
- Hoskin, A. (2011). Household gun prevalence and rates of violent crime: A test of competing

- gun theories. *Criminal Justice Studies*, 24(1): 125-136. doi: 10.1080/1478601X.2011.544445.
- Hsu, H-T., Fulginiti, A., Petering, R., Barman-Adhikari, A., Bedell, K., Ferguson, K.M., Narendorf, S.C., Shelton, J., Santa Maria, D., Bender, K., & Rice, E. (2021). *American Journal of Preventive Medicine*, 61(4): 585-590. <https://doi.org/10.1016/j.amepre.2021.02.016>.
- Jackson, K., & Cowan, R. (2022). *U.S. House Passes Gun-Safety Legislation as Court Expands Gun Rights*. Reuters. Retrieved July 2, 2022 from <https://www.reuters.com/world/us/landmark-gun-safety-bill-heads-us-house-after-senate-passage-2022-06-24/>.
- Jeannotte, M.S. (2003). Singing alone? The contribution of cultural capital to social cohesion and sustainable communities. *International Journal of Cultural Policy*, 9: 35-49.
- Johnson, B.T., Sisti, A., Bernstein, M., Chen, K., Hennessy, E.A., Acabchuk, R.L., & Matos, M. (2021). Community-level factors and incidence of gun violence in the United States, 2014-2017. *Social Science and Medicine*, 280: 1-10. <https://doi.org/10.1016/j.socscimed.2021.113969>.
- Johnston, M.P. (2014). Secondary data analysis: A method of which the time has come. *Qualitative and Quantitative Methods in Libraries*, 3: 619-626.
- Kamal, R. D., & Burton, C. (2018). Policy gridlock versus policy shift in gun politics: A comparative veto player analysis of gun control policies in the United States and Canada. *World Affairs*, 181(4): 317-347. <https://doi-org.libproxy.wlu.ca/10.1177/0043820018814356>.
- Kawachi, I., Kennedy, B. P., & Wilkinson, R. G. (1999). Crime: Social disorganization and

- relative deprivation. *Social Science and Medicine*, 48: 719-731.
- Kubrin, C. E., & Weitzer, R. (2003). New directions in social disorganization theory. *Journal of Research in Crime and Delinquency*, 40(4): 374-402. doi: 10.1177/0022427803256238.
- Kumar, M. & Moledina, A. (2017, June 13). *Mobility Studies: An Inclusive Interdisciplinary Approach to Understanding Migration*. Challenging Borders.
<https://challengingborders.wooster.edu/blog/tag/mobility-vs-migration/>.
- Lawson, E. (2012). Single mothers, absentee fathers, and gun violence in Toronto: A contextual interpretation. *Women's Studies*, 41: 805-828. doi: 10.1080/00497878.2012.707903.
- Lemieux, F. (2014). Effect of gun culture and firearm laws on gun violence and mass shootings in the United States: A multi-level quantitative analysis. *Journal of Criminal Justice Sciences*, 9(1): 74-93.
- Lott, A.J., & Lott, B.E. (1966). Group cohesiveness and individual learning. *Journal of Educational Psychology* 57: 61–73. doi:10.1037/h0023038.
- Mekoa, I., & Busari, D. (2018). Social cohesion: Its meaning and complexities. *Journal of Social Sciences*, 14(1): 107-115. doi: 10.3844/jssp.2018.107.115.
- Michalopoulos, S. (2012). The origins of ethnolinguistic diversity. *The American Economic Review*, 102(4): 1508-1539. <https://www.jstor.org/stable/23245463>.
- Murray, B.L. (2003). Qualitative research interviews: Therapeutic benefits for the participants. *Journal of Psychiatric and Mental Health Nursing*, 10: 231-238.
- National Criminal Justice Reference Service. (1994, October 24). *Violent Crime Control and Law Enforcement Act of 1994*. <https://www.ncjrs.gov/txtfiles/billfs.txt>.
- Oraka, E., Thummalapally, S., Anderson, L., Burgess, T., Seibert, F., & Strasser, S. (2019). A

- cross-sectional examination of US gun ownership and support for gun control measures: Sociodemographic, geographic, and political associations explored. *Preventative Medicine*, 123: 179-184. <https://doi.org/10.1016/j.ypmed.2019.03.021>.
- Ou, S-R., Mersky, J.P., Reynolds, A.J., & Kohler, K.M. (2007). Alterable predictors of educational attainment, income, and crime: Findings from an inner-city cohort. *The University of Chicago Press Journals*, 81(1): 85-128. <https://www.jstor.org/stable/10.1086/510783>.
- Pallant, J. (2016). *SPSS Survival Manual: A step by step guide to data analysis using IBM SPSS*. Open University Press.
- Parsons, T. (2013). *Social System*. London: Routledge.
- Piscitelli, A., & Doherty, S. (2018). Connecting social disorganization to broken windows and routine activities. *The Canadian Geographer*, 62(4): 589-596. doi: 10.1111/cag.12468.
- Rakove, J. N. (2002). Words, Deeds, and Guns: 'Arming America' and the Second Amendment. *The William and Mary Quarterly*, 59(1): 205 – 210. doi: <https://www.jstor.org/stable/3491652>.
- Rowan, Z.R., Schubert, C.A., Loughran, T.A., Mulvey, E.P., & Pardini, D.A. (2019). Proximal predictors of gun violence among adolescent males involved in crime. *Law and Human Behaviour*, 43(3): 250-262. <http://dx.doi.org/10.1037/lhb0000327>.
- Sampson, R. J., & Groves, W. B. (1989). Community structure and crime: Testing social-disorganization theory. *American Journal of Sociology*, 94(4): 774 – 802.
- Sampson, R. J., Raudenbush, S. W., & Earls, F. (1997). Neighbourhoods and violent crime: A multilevel study of collective efficacy. *American Association for the Advancement of Science*, 277(5328): 918 – 924. <https://www.jstor.org/stable/2892902>.

- Shaw, C. R., & McKay, H. D. (1942). *Juvenile delinquency and urban areas*. Chicago: University of Chicago Press.
- Siegel, M., Goder-Reiser, M., Duwe, G., Rocque, M., Fox, J.A., & Fridel, E.E. (2020). The relation between state gun laws and the incidence and severity of mass public shootings in the United States, 1976-2018. *Law and Human Behaviour*, 44(5): 347-360. <http://dx.doi.org/10.1037/lhb0000378>.
- Siegel, M., Pahn, M., Xuan, Z., Fleegler, E., & Hemenway, D. (2019). The impact of state firearm laws on homicide and suicide deaths in the USA, 1991-2016: A panel study. *Journal of General Internal Medicine*, 34(10): 2021-2028. doi: 10.1007/s11606-019-04922-x.
- Social Policy, Analysis & Research. (2022). *Getting to know 'Neighbourhood Profiles'*. City of Toronto.
- Stanick, C.F., Crosby, L.K., & McDonald, M.K. (2017). Family Disruption. In S. Goldstein & M. DeVries (Eds.), *Handbook of DSM-5 disorders in children and adolescents*.(pp. 583-595). Springer.
- Stanley, D. (2003). What do we know about social cohesion: The research perspective of the federal government's social cohesion research network. *The Canadian Journal of Sociology*, 28(1): 5-17. <https://www.jstor.org/stable/3341872>.
- Statistics Canada. (2015). Section 3: Dictionary of concepts and definitions. Retrieved December 6, 2021 from <https://www150.statcan.gc.ca/n1/pub/71-543-g/2012001/part-partie3-eng.htm>
- Statistics Canada. (2016, September 16). *Classification of Marital Status*. <https://www23.statcan.gc.ca/imdb/p3VD.pl?Function=getVD&TVD=252495>.

- Statistics Canada. (2017a, August 2). *Families Reference Guide, Census of Population, 2016*.
<https://www12.statcan.gc.ca/census-recensement/2016/ref/guides/002/98-500-x2016002-eng.cfm>.
- Statistics Canada. (2017b, November 29). *Mobility and Migration Reference Guide, Census of Population, 2016*. <https://www12.statcan.gc.ca/census-recensement/2016/ref/guides/010/98-500-x2016010-eng.cfm>.
- Statistics Canada (2022a, July 4). *Firearm-related violent crime, 2009 to 2017 - Archived*.
<https://www150.statcan.gc.ca/n1/en/pub/89-28-0001/2018001/article/00004-eng.pdf?st=JklJWMy->.
- Statistics Canada (2022b, June 28). *Data*. <https://www150.statcan.gc.ca/n1/en/type/data?MM=1>.
- Steenbeek, W., & Hipp, J. R. (2011). A longitudinal test of social disorganization theory: Feedback effects among cohesion, social control and disorder. *American Society of Criminology, 49*(3): 833 – 871. doi: 10.1111/j.1745-9125.2011.00241.x.
- Steidley, T., Ramey, D. M., & Shrider, E. A. (2017). Gun shops as local institutions: Federal firearms licensees, social disorganization and neighbourhood violent crime. *Social Forces, 96*(1): 265-298. doi: 10.1093/sf/sox039.
- Stevens, J. (1996). *Applied multivariate statistics for the social sciences* (3rd edn). Mahwah, NJ: Lawrence Erlbaum.
- Stewart, D.W., & Kamins, M.A. (1993). *Secondary research: Information sources and methods*. Newbury Park, CA: Sage.
- Tabachnick, B.G. & Fidell, L.S. (2013). *Using multivariate statistics* (6th edn). Boston: Pearson Education.
- The Texas Tribune. (2022). *Uvalde School Shooting*. Retrieved July 2, 2022 from

<https://www.texastribune.org/series/uvalde-texas-school-shooting/>.

Wex. (2022). *Second Amendment*. Legal Informational Institute. Retrieved July 2, 2022 from

https://www.law.cornell.edu/wex/second_amendment.

Winterdyk, J. 2020. *Canadian Criminology, 4th Edition*. Oxford University Press.

Yamane, D. (2017). The sociology of U.S. gun culture. *Sociology Compass*, 11(7).

<https://doi-org.libproxy.wlu.ca/10.1111/soc4.12497>.

Yardley, L., & Bishop, F.L. (2015). Using mixed methods in health research: Benefits and challenges. *British Journal of Health Psychology*, 20: 1-4. doi:10.1111/bjhp.12126.