

The Effects of Alcohol Access on the Spatial and Temporal Distribution of Crime

by

Jessica Laura Fitterer
MSc, University of Victoria, 2012
BSc, University of Victoria, 2009

A Dissertation Submitted in Partial Fulfillment
of the Requirements for the Degree of

DOCTOR OF PHILOSOPHY

in the Department of Geography

© Jessica Laura Fitterer, 2017
University of Victoria

All rights reserved. This dissertation may not be reproduced in whole or in part, by
photocopy or other means, without the permission of the author.

Supervisory Committee

The Effects of Alcohol Access on the Spatial and Temporal Distribution of Crime

by

Jessica Laura Fitterer
MSc, University of Victoria, 2012
BSc, University of Victoria, 2009

Supervisory Committee

Dr. Trisalyn Nelson, Supervisor
(Department of Geography, University of Victoria)

Dr. Aleck Ostry, Committee Member
(Department of Geography, University of Victoria)

Dr. Timothy Stockwell, Outside Member
(Department of Psychology, University of Victoria)

Abstract

Supervisory Committee

Dr. Trisalyn Nelson, Supervisor
(Department of Geography, University of Victoria)

Dr. Aleck Ostry, Committee Member
(Department of Geography, University of Victoria)

Dr. Timothy Stockwell, Outside Member
(Department of Psychology, University of Victoria)

Increases in alcohol availability have caused crime rates to escalate across multiple regions around the world. As individuals consume alcohol they experience impaired judgment and a dose-response escalation in aggression that, for some, leads to criminal behaviour. By limiting alcohol availability it is possible to reduce crime; however, the literature remains mixed on the best practices for alcohol access restrictions. Variances in data quality and statistical methods have created an inconsistency in the reported effects of price, hour of sales, and alcohol outlet restrictions on crime. Most notably, the research findings are influenced by the different effects of alcohol establishments on crime. The objective of this PhD research was to develop novel quantitative approaches to establish the extent alcohol access (outlets) influences the frequency of crime (liquor, disorder, violent) at a fine level of spatial detail (x,y locations and block groups). Analyses were focused on British Columbia's largest cities where policies are changing to allow greater alcohol access, but little is known about the crime-alcohol access relationship. Two reviews were conducted to summarize and contrast the effects of alcohol access restrictions (price, hours of sales, alcohol outlet density) on crime, and evaluate the state-of-the-art in statistical methods used to associate crime with alcohol availability. Results highlight key methodological limitations and fragmentation in alcohol policy effects on

crime across multiple disciplines. Using a spatial data science approach, recommendations were made to increase spatial detail in modelling to limit the scale effects on crime-alcohol association. Providing guidelines for alcohol-associated crime reduction, kernel density space-time change detection methods were also applied to provide the first evaluation of active policing on alcohol-associated crime in the Granville St. entertainment district of Vancouver, British Columbia. Foot patrols were able to reduce the spatial density of crime, but hot spots of liquor and violent assaults remained within 60m proximity to bars (nightclubs). To estimate the association between alcohol establishment size, and type on disorder and violent crime reports in block groups across Victoria, British Columbia a Poisson Generalized Linear Model with spatial lag effects was applied. Estimates provided the factor increase (1.0009) expected in crime for every additional patron seat added to an establishment capacity, and indicated that establishments should be spaced greater than 300m apart to significantly reduce alcohol-associated crime. These results offer the first evaluation of seating capacity and establishment spacing on alcohol-associated crime for alcohol license decision making, and are pertinent at a time when alcohol policy reform is being prioritized by the British Columbia government. In summary, this dissertation contributes 1) cross-disciplinary policy and methodological reviews, 2) expands the application of spatial statistics to alcohol-attributable crime research, 3) advances knowledge on local scale of effects of different alcohol establishment types on crime, 4) and develops transferable models to estimate the effects of alcohol establishment seating capacity and proximity between establishments on the frequency of crime.

Table of Contents

Supervisory Committee	ii
Abstract	iii
Table of Contents	v
List of Tables	vii
List of Figures	viii
Acknowledgments	ix
Dedication	x
Co-authorship statement	xi
1 Chapter 1	1
1.1 Introduction	1
1.1.1 Alcohol access and crime	1
1.1.2 Alcohol establishments and crime	1
1.1.3 Scope of analysis	2
1.1.4 Objectives and content summary	3
2 Chapter 2	5
2.1 Introduction	6
2.2 Methods	8
2.2.1 Study selections	8
2.2.2 Study synthesis	8
2.3 Results	9
2.3.1 Study selections	9
2.3.2 Study designs	10
2.3.3 Violent crime data	11
2.3.4 Methodologies	12
2.4 Policy results	15
2.4.1 Alcohol price and violent crime	15
2.4.2 Alcohol trading hours and violent offences	15
2.4.3 Alcohol outlet density and violent offences	16
2.5 Discussion	17
2.5.1 Policy synthesis	17
2.5.2 Study design considerations	21
2.5.3 Geographic perspective for future research	23
2.5.4 Conclusion	26
3 Chapter 3	28
3.1 Introduction	29
3.2 Study selection and synthesis	30
3.3 Results	33
3.3.1 Data	33
3.3.2 Spatial units	34
3.3.3 Dataset structure	36
3.4 Statistical approaches	36
3.4.1 Autoregressive integrated moving average	36
3.4.2 Generalized Linear Model	36

3.4.3	Hierarchical, non-linear models and extensions	38
3.4.4	Regression Trees, Cluster Detection, and Mapping.....	43
3.5	Discussion.....	44
3.5.1	Methods.....	44
3.5.2	Future research.....	52
3.6	Conclusion	57
4	Chapter 4.....	58
4.1	Introduction.....	58
4.2	Methods.....	60
4.2.1	Study area.....	60
4.2.2	Data	61
4.2.3	Spatial analysis.....	63
4.2.4	Temporal analysis	65
4.3	Results.....	66
4.3.1	Change in the spatial patterns of crime in the GEA.....	66
4.3.2	Change in the temporal patterns of crime in the GEA.....	70
4.4	Discussion	73
4.4.1	Active policing effects	73
4.4.2	Implications for alcohol policy	75
4.4.3	Study considerations	76
4.5	Conclusion	76
5	Chapter 5.....	78
5.1	Introduction.....	79
5.2	Methods.....	81
5.2.1	Study area.....	81
5.2.2	Geographic unit.....	83
5.2.3	Crime.....	85
5.2.4	Covariates	85
5.2.5	Spatial Lag Model.....	88
5.2.6	Model validation	88
5.2.7	Distance modelling	89
5.3	Results.....	90
5.3.1	Crime in Victoria	90
5.3.2	Model validation results.....	92
5.3.3	Estimation results.....	92
5.3.4	Distance analysis.....	93
5.4	Discussion	94
5.5	Conclusion	97
6	Chapter 6.....	98
6.1	Conclusions.....	98
6.2	Key findings for crime reduction.....	102
6.3	Future research.....	102
	Bibliography	105

List of Tables

Table 2.1 Count of publications by country of analyses.....	10
Table 2.2 Source of violent crime statistics	12
Table 2.3 Types of violent crimes/injuries studied.....	12
Table 2.4 Studies categorized by applied spatial units	13
Table 2.5 Summary results of the selected publications. Presented are the percent of studies reporting significant/substantive policy effects on violent injury/crime categorized by study design, policy type, and combined policy types.....	17
Table 3.1 Search term descriptions.....	31
Table 3.2 Country study areas	33
Table 3.3 Applied analysis units counted by country, overall use before and after 2009, and the percent change in use after 2009. Percent change in use was calculated by subtracting the proportion of studies applying the analysis unit before 2009 from the proportion of studies applying the same unit after 2009.....	35
Table 3.4 Applied quantitative methods	46
Table 4.1 Poisson GLM modelling results. Policing intervention was a significant factor in the reduction of liquor infractions, but not assaults.....	73
Table 5.1 Summary of covariates used to model and predict violent and disorder crimes across the 138 dissemination areas	84
Table 5.2 Model estimates, coefficients evaluated at $p < .05$ level.	93

List of Figures

Figure 3.1 Study selection criteria	32
Figure 4.1 Displayed are the locations of liquor primary licenses of on-premises drinking establishments within the Granville Street Entertainment Area of Vancouver British Columbia Canada. Liquor establishment data were downloaded from the British Columbia Liquor Distribution Branch. Hotels are prominent in the south-west end and nightclubs in the north-east end.	61
Figure 4.2 displays the change in the spatial density of liquor infractions since 2006. On the left side are the spatial density maps of crime data from 2006 to the change year (2010 and 2013). On the right are the kernel density change maps. Black delineates a two standard deviation increase in spatial density of crime, while red symbolizes a decrease.	67
Figure 4.3 displays the change in the spatial density of assaults since 2006. On the left side are the spatial density maps of crime data from 2006 to the change year (2010 and 2013). On the right are the kernel density change maps. Black delineates a two standard deviation increase in spatial density of crime, while red symbolizes a decrease.	69
Figure 4.4 displays the temporal pattern of liquor infractions in the GEA. In the daily frequency graph, day 1 is Monday. In the active policing graph the frequency includes infractions occurring early morning Saturday and Sunday between May to September each year.	71
Figure 4.5 displays the temporal pattern of assaults in the GEA. In the daily frequency graph, day 1 is Monday. In the active policing graph the frequency includes infractions occurring early morning Saturday and Sunday between May to September each year....	72
Figure 5.1 Victoria study area displaying the spatial distribution of crime and alcohol establishments. Off-premises licenses include government and independent retail liquor stores, and ubrews. On-premises licenses include establishments where drinking is the primary activity (bars and pubs), and where drinking is a subsidiary activity in restaurants, lounges, theatres, clubs, and hotels (on-premises). For mapping purposes, we differentiated bars as primary drinking establishments with a dance floor.	82
Figure 5.2 Observed and predicted counts of violent and disorder crime reports on Friday and Saturday nights between 7:00pm and 4:00am from January 16 th 2015 and May 29 th 2016.....	91
Figure 5.3 Frequency of violent and disorder crime reports between 7:00pm and 4:00am Friday and Saturday night from January 16 th 2015 and May 29 th 2016.	91
Figure 5.4 Influence of bar and pub proximity (distance in meter) on the frequency of violent and disorder crime around bars and pubs.	94

Acknowledgments

I would like to thank my supervisor, Dr. Trisalyn Nelson, for her unwavering academic and personal support over the last six years. There are no words to express the gratitude I feel for the opportunities you presented, and how enjoyable you made my graduate studies experience. Trisalyn, you pushed me to achieve goals I never thought possible, and instilled a level of confidence in me that I will hold dear for the rest of my life.

To my committee member, Dr. Timothy Stockwell, thank you for welcoming me to a world of alcohol policy research. I appreciated your guidance, support, and timely responses in the generation of manuscripts. Special thanks are also awarded to Ryan Prox, from Vancouver Police Department, who provided crime data for our Granville Street Entertainment District analysis.

To my SPAR-laboratory mates past and present I thank you. Colin Robertson, Jed Long, Nick Gralewicz, Ben Stewart, Karen Laberee, Kathryn Morrison, Keith Holmes, Mathieu Bourbonnais, Shanley Thompson, Cesar Suarez, Liliana Perez, Michael Branion-Calles, Ben Jestico, Robin Kite, and Gillian Harvey I am so fortunate to have met you. I love that I can still call upon your diverse strengths to problem solve new challenges in my life. Particularly, I would like to recognize Robin and Gillian for helping me “hold it together” in the final days of my PhD research.

To my loving family, who made so many sacrifices to ensure my academic success: Mom, thank you for the countless hours you spent editing my work, and assuring me I would get through every challenge. Dad, thank you for inspiring my love for science and thirst for problem solving. Finally, I would like to thank my adoring husband. Matthew, you were the foundation of my PhD success, keeping our family afloat financially and emotionally as I pursued my academic dream. Thank you for your continued patience as I spent most of our free time working or thinking about my research. I love you.

Dedication

I dedicate my dissertation to my daughter, Penelope Lynn Fitterer. I hope you live your life fearlessly. Follow your dreams with determination and passion, and the rest of life's joys will follow.

Co-authorship statement

Chapters 2 through 5 of this dissertation compose manuscripts that were co-authored. The following outlines contributions of the doctoral candidate, and each of the authors. A reference representing the publication status of each chapter is provided.

Chapter 2

Fitterer, J. L., Nelson, T. A., & Stockwell, T. (2015). A Review of Existing Studies Reporting the Negative Effects of Alcohol Access and Positive Effects of Alcohol Control Policies on Interpersonal Violence. *Frontiers in Public Health*, 3, 1–11.

JF designed the review structure, performed the literature search and synthesis, and prepared the manuscript for publication. TS provided the concept of work, and TN aided in the preparation of the manuscript with comments, edits, and advice on structure.

Chapter 3

Fitterer, J. L., & Nelson, T. A. (2015). A Review of the Statistical and Quantitative Methods Used to Study Alcohol-Attributable Crime. *Plos One*, 10(9), e0139344.

JF designed the review structure, performed the literature search and synthesis, and prepared the manuscript for publication. TN aided in the preparation of the manuscript with comments, edits, and advice on structure and content of the spatial analysis critique.

Chapter 4

Fitterer, J. L., Nelson, T. A., & Stockwell, T. (In Review). The positive effects of increased foot patrols on the incidence of liquor infractions and assaults in the Granville Street Entertainment Area of Vancouver British Columbia Canada. *Applied Geography*, JAPG_2016_252.

JF developed the concept of work, conducted analysis, and prepared the manuscript for publication. TN aided in obtaining crime data. TN and TS provided comments, edits, and advice on structure and content during the preparation of the manuscript.

Chapter 5

Fitterer, J. L., Nelson, T. A., & Stockwell, T. (In Preparation). The negative effects of alcohol establishment size on the frequency of violent and disorder crime across block groups of Victoria, British Columbia.

JF developed the concept of work, obtained data, conducted analysis, and prepared the manuscript for publication. TN and TS provided comments, edits, and advice on structure during the preparation of the manuscript.

1 Chapter 1

1.1 Introduction

1.1.1 Alcohol access and crime

Increases in alcohol access have led to higher rates crime across multiple regions (Resko et al. 2010; Gorman et al. 2005; Parker et al. 2011; Nielsen & Martinez 2006; Liang & Chikritzhs 2011; Livingston 2008). As people consume alcohol they experience impaired judgement and a dose-response escalation in aggression that for some leads to criminal behaviour (Duke et al. 2011; Felson & Staff 2010). By decreasing price, extending the hours of sales, and increasing the number of alcohol establishments, populations have seen higher rates of impaired driving (Gruenewald et al. 2002), nuisance (Kypri et al. 2008), property damage (Wilkinson & Livingston 2012), and violent crime (Gruenewald et al. 2006; Lipton & Gruenewald 2002; Mazerolle et al. 2012). However, the literature remains mixed on the best practices for alcohol access restrictions. Variances in data quality and statistical methods have created an inconsistency in the reported effects of alcohol price, hours of sale, and alcohol outlet restrictions on crime (Popova et al. 2009; Campbell et al. 2009; Stockwell & Chikritzhs 2009; Fitterer et al. 2015). Most notably, the research findings are influenced by the different effects of on (e.g., pubs, bars/nightclubs, lounges, clubs, theatres, restaurants) and off (government and private liquor stores, off-sale licenses) premises alcohol establishment licenses on crime (Fitterer et al. 2015).

1.1.2 Alcohol establishments and crime

Alcohol establishments escalate crime by providing alcohol access, and a place where intoxicated patrons can interact under impaired judgement (Livingston et al. 2007). Clusters of alcohol outlets in industrial/commercial districts can attract a steady stream of crime offenders and targets (Pridemore & Grubestic 2012a; Brantingham 1993), and particular drinking venues will entice groupings of crime-prone clientele (Gruenewald 2007; Livingston et al. 2007). This explains why crime clusters around alcohol

establishments. For example, bars that are over-crowded, loud, and over-serve alcohol are prime locations for alcohol-attributable crime (Green & Plant 2007; McFadden et al. 2015).

To set alcohol licensing policy for crime reduction, decision makers need to know what establishment restrictions are most effective. Some options include: restricting establishments by type, increasing the space between venues, and limiting seating capacity. Currently, the literature reports differences in the influence of alcohol establishment types on crime (Fitterer et al. 2015). Only a small body of research has studied how crime clusters around different drinking establishments (White et al. 2015; Ratcliffe 2012; Burgess & Moffatt 2011; Grubestic & Pridemore 2011), and it is not well understood how the size (patron capacity) of on-premises alcohol establishments increases crime (Fitterer & Nelson 2015) as the majority of studies measure outlet exposure as a count per area, population, or roadway mile (Fitterer & Nelson 2015; Grubestic et al. 2016). Therefore, more studies are needed to understand how crime is affected by the type, proximity, and size of alcohol establishments.

1.1.3 Scope of analysis

British Columbia's largest cities (Vancouver and Victoria) were the focus of analyses for this dissertation due to the low number of studies quantifying the association between alcohol establishments and crime, and the changing alcohol access policy. We know that within British Columbia increases in off-premise alcohol outlets caused higher rates of sales (Stockwell et al. 2009) and human mortality (Stockwell et al. 2011). However, less is known about the implications of different types of alcohol establishments on the spatial and temporal patterns of crime. One publication quantifies the impact of privatization of alcohol stores on traffic violations and crimes against a person across British Columbia, at an aggregated spatial scale (Stockwell et al. 2015), but more local analysis is needed. Despite the gap in information, municipal governments evaluate the public safety risk of new establishments in the absence of provincial population restrictions of on-premises alcohol outlet densities (Giesbrecht et al. 2013). For some municipalities this means evaluating densities and crime within 100m, 300m,

500m radii to approve developments (City of Victoria 2012b) or setting minimum cluster allowances of 50m to 500m (Matthews 2009) in an ad hoc manner.

Without clear regulations on the density and spacing of alcohol establishments, the popularity of liberalizing alcohol access is prevalent and a key mandate of the British Columbia government. Recent changes in government policy have led to the introduction of happy hours, removal of consumption barriers at festivals, and allowance of local liquor manufacturers to sell products on site (Government of British Columbia 2015b). In addition to the current allowance of late night sales (4:00am), lower than normal alcohol pricing (Kendall 2008), and on-premises licence developments (Giesbrecht et al. 2013) there is a growing public safety concern. Annually it is estimated that 17,888 violent crimes, 23,954 property crimes, and 26,439 other offences in British Columbia are alcohol-attributable (Fitterer 2013).

1.1.4 Objectives and content summary

To support alcohol license decision making for crime reduction, the objective of my PhD research was to develop novel quantitative approaches to establish the extent alcohol access (outlet types and size) influence the frequency of crime (liquor, disorder, violent). I used crime data at a fine level of spatial detail (x,y locations and block groups) to build results that can inform crime management in British Columbia and form evidence for alcohol establishment licensing decisions globally. I integrated spatial analysis, and distance decay modelling to expose other disciplines (health policy) to new level of detail in crime-alcohol access research.

Chapter 2 and 3 reviews were conducted to summarize and contrast the effects of alcohol access restrictions (alcohol price, hours of sales, outlet density) on crime, and evaluate the state-of-the-art in statistical methods used to associate crime with alcohol availability. Where previous reviews have focused on one (Wagenaar et al. 2010; Stockwell & Chikritzhs 2009) or two (Popova et al. 2009) alcohol access influences I evaluated effectiveness of price, trading hours, and alcohol outlet density on violent crime simultaneously, and provided a comprehensive methods critique. Results highlight key methodological limitations and fragmentation in alcohol policy effects on crime across multiple disciplines. Using a spatial data science approach, recommendations were

made to increase spatial detail in modelling to limit the scale effects on the crime-alcohol association.

Chapter 3 provides guidelines for alcohol-associated crime reduction. I conducted a novel application of Bowman & Azzalini (1997) kernel density change detection method to provide the first evaluation of active policing on alcohol-associated crime in the Granville St. entertainment district of Vancouver, British Columbia. Key results found that police foot patrols were able to significantly reduce the spatial density of crime ($p < .05$). Hot spots of liquor and violent assaults remained within 60m proximity to bars (nightclubs), but dissipated around other on-premises licenses.

Chapter 5 estimated the association between alcohol establishment size, and type on disorder and violent crime reports in block groups across Victoria, British Columbia using a Poisson Generalized Linear Model with spatial lag effects. Estimates provided the factor increase (1.0009) expected in crime for every additional patron seat added to an establishment capacity, and indicated that establishments should be spaced greater than 300m apart to significantly reduce alcohol-associated crime (disorder and violent offences). These results provide the first evaluation of seating capacity and establishment spacing on alcohol-associated crime for alcohol license decision making, and are pertinent at a time when alcohol policy reform is being prioritized by the British Columbia government. Models provide transferable methods for estimating the effects of establishment seating capacity and spacing on crime in other cities, and support research that identifies bars as the problem venues for criminal offences (e.g., (Mair et al. 2013; Lipton & Gruenewald 2002; Gruenewald & Remer 2006; Ratcliffe 2012; Conrow et al. 2015; Crandall et al. 2015; Cameron et al. 2015)).

Chapter 6 provides a summary of the dissertation contributions including: 1) cross-disciplinary policy and methodological reviews, 2) expanding the application of spatial statistics to alcohol-attributable crime research, 3) making advances in the knowledge of local scale of effects of different alcohol establishment types on crime and 4) developing transferable models to estimate the effects of alcohol establishment seating capacity and proximity between establishments on the frequency of crime.

2 Chapter 2

A review of existing studies reporting the negative effects of alcohol access and positive effects of alcohol control policies on interpersonal violence

Abstract

Alcohol consumption often leads to elevated rates of violence yet alcohol access policies continue to relax across the globe. Our review establishes the extent alcohol policy can moderate violent crime through alcohol availability restrictions. Results were informed from comprehensive selection of peer-reviewed journals from 1950 to October 2015. Our search identified 87 relevant studies on alcohol access and violence conducted across 12 countries. Seventeen studies included quasi-control design, and 23 conducted intervention analysis. Seventy-one (82%) reported a significant relationship between alcohol access and violent offences. Alcohol outlet studies reported the greatest percentage of significant results (93%), with trading hours (63%), and alcohol price following (58%). Results from baseline studies indicated the effectiveness of increasing the price of commonly consumed alcohol, restricting the hours of alcohol trading, and limiting the number of alcohol outlets per region to prevent violent offences. Unclear are the effects of tax reductions, restriction of on-premises re-entry, and different outlet types on violent crime. Further, the generalization of statistics over broad areas and the low number of control/intervention studies poses some concern for confounding or correlated effects on study results, and amount of information for local level prevention of interpersonal violence. Future studies should focus on gathering longitudinal data, validating models, limiting crime data to peak drinking days and times, and wherever possible collecting the joint distribution between violent crime, intoxication, and place. A greater up take of local level analysis will benefit studies comparing the influence of multiple alcohol establishment types by relating the location of a crime to establishment proximity. Despite, some uncertainties particular studies showed that even modest policy changes such as 1% increases in alcohol price, one hour changes to closing times, and

limiting establishment densities to less than 25 outlets per postal code substantively reduce violent crime.

2.1 Introduction

Alcohol access and consumption has contributed to escalated levels of violence including domestic (Cunradi et al. 2012; M. Livingston 2011; McKinney et al. 2009; Waller et al. 2012), sexual (Schofield & Denson 2013), and interpersonal assaults (Chikritzhs & Stockwell 2002; Mair et al. 2013; Livingston 2008; Lipton & Gruenewald 2002). Consistent effects are represented by a comprehensive evaluation of 563 injury cases from 16 different countries showing that intoxicated patients had a higher likelihood of a violence-related injury than any other cause (Macdonald et al. 2005). Generally, the risk of interpersonal violence increases with the frequency and volume of alcohol consumption (Barnwell et al. 2006; Lightowers et al. 2013; Connor et al. 2011), and in relation to certain types of drinking environments and activities (Hughes et al. 2008; Newton & Hirschfield 2009; Briscoe & Donnelly 2003; Livingston et al. 2007; Chikritzhs & Stockwell 2002; Mazerolle et al. 2012; Chikritzhs & Stockwell 2007; Green & Plant 2007; Hughes et al. 2011). For instance, consuming alcohol in a restaurant is unlikely to lead to alcohol-related violence (Freisthler et al. 2004; Gruenewald et al. 2006), whereas intoxicated patrons inside and around bars have created spatial clusters of violent offences in these areas (Nicholas et al. 2007; Chikritzhs & Stockwell 2002).

The relationship between alcohol availability and violence is complex, including an individual's biochemical, psychological, and social responses to alcohol consumption and their environment. Researchers have established that intoxication ignites violent behaviour in those predisposed to aggression (Felson et al. 2008) and theorize that consumption leads to weakened inhibitions (see (Exum 2006)) and relaxed normative behaviour (i.e., perceived allowance of aggression) causing the increased risk of alcohol-related violence inside and around drinking premises (Gorman et al. 2013). Considering place based theories it is also likely that alcohol serving establishments attract perpetrators of violent crime by grouping targets for victimization, ultimately leading to clusters of crime in regions with greater alcohol availability (e.g., routine activity theory,

(Brantingham 1993; Gorman et al. 2013)). For these reasons, policies that manage alcohol consumption and interaction of intoxicated persons are paramount for public safety.

Relaxing the mechanisms that control the availability of alcohol is likely to increase violent offences by yielding higher consumption and promoting intoxicated high-risk patrons to interact (Babor et al. 2010). Increases in violence have been linked with decreased alcohol prices (Fogarty 2006; Gallet 2007; Wagenaar et al. 2010), extended trading hours (Chikritzhs & Stockwell 2002; Stockwell & Chikritzhs 2009), and increased alcohol outlets densities (Popova et al. 2009; Stockwell et al. 2009; Campbell et al. 2009) including both on (e.g., taverns, hotels, bars, pubs, and clubs) and off (e.g., retail stores, off sales) retailers; though, alcohol availability continues to rise in many regions worldwide (Crombie et al. 2007; Stockwell et al. 2009; Giesbrecht 2006; Giesbrecht et al. 2011; Popova et al. 2009; Babor et al. 2010). The trend in policy relaxation indicates a need to synthesize the effects of alcohol access on violent offences to inform those tasked with improving public health and safety.

The goal of our review was to summarize the effects of alcohol policy on violent offences through restrictions on alcohol availability. We extend the findings of existing alcohol policy reviews. First, by evaluating the effectiveness of price, trading hours, and alcohol outlet density on violent crime simultaneously, where previous reviews have focused on one (Wagenaar et al. 2010; Stockwell & Chikritzhs 2009) or two (Popova et al. 2009) alcohol access influences. Secondly, we update the syntheses of alcohol policy effects, which have seen a considerable increase in publication since 2010 rising from one to five publications per year between 1995 and 2010 to ~12 a year afterward. Using a health geography perspective, we provide a brief critique on the quality of study designs, data (sources and aggregation), geographic scale, and methods. We suggest ways to improve evidence-based information for decision making, and highlight areas of uncertainty for future policy studies to address.

2.2 Methods

2.2.1 Study selections

Using the web of science and google scholar, we performed a comprehensive search of the available literature using a combination of key terms integrated in the following Boolean query: “([(alcohol tax* OR alcohol cost* OR alcohol price* OR alcohol outlet* OR alcohol outlet density* OR alcohol trading hours OR alcohol sales OR alcohol availability OR licensing OR bars* OR pubs* OR hotels* OR on-premises OR off-premises) AND (violence OR assault* OR domestic violence OR homicide OR interpersonal violence OR rape)])”. We searched available studies from January 1950 to October 2015 resulting in 888 selections, which we refined to 798 after excluding reviews, editorial materials, and meeting abstracts to focus on primary research. From the 798 studies, we excluded studies reporting the effects of alcohol access policy on crimes other than violence and studies that associated alcohol consumption/ access other than price, trading hours, or outlet outlets to violent crime/injuries. Our final selection of 87 studies included papers that analyzed a change or cross-sectional assessment of the effects of alcohol tax, price, hours of trading, or establishment density on violent injury or crime data.

2.2.2 Study synthesis

Studies were summarized by author, date of publication, place, and year(s) of study. Outcome variable, exposure variables, study design, control data, and key findings were recorded. Any statistical concerns were noted. To demonstrate the quality of information available for alcohol price, trading hour, and outlet density policy decision-making we quantified the proportions of intervention (i.e., quasi control studies), panel, time-series, and cross-sectional datasets. We considered the range of countries represented by analysis and if data distributions were mapped over time and space to facilitate the interpretation of data and results for policy makers, health, and police personnel. We also considered the frequency of researchers using control groups or the independent effects of demographics, socio-economics, and concurrent polices on violent occurrences.

To evaluate study quality, and address gaps in analysis techniques, we summarized data sources and modelling methods. For the outcome variable, we considered the source of information and if the violent event data were directly alcohol-attributable. To assess overall power of the statistical analyses, we considered how data (outcome and exposure) were aggregated over analysis units (e.g., census tract versus block groups) and time. We indicated prominent statistical models and if spatial or temporal dependence was tested or modelled to control for biased reductions in standard errors (Millar & Gruenewald 1997). We monitored if studies using short time-periods (e.g., consumption in previous months) or small geographic units (e.g., alcohol outlets in neighbouring communities) included lagged temporal (e.g., alcohol consumption in previous time period) or spatial effects (e.g., number of alcohol outlets in neighbouring regions) when estimating violent occurrences.

We synthesized alcohol policy findings by dataset structure. Categories included: cross-sectional (data collected or aggregated over one time period, representing multiple individuals or regions), time-series (individual or aggregated data collected from one region over time), panel (aggregated data collected over multiple regions and time-periods), or intervention (data collected before and after an alcohol policy change, either in a time-series or panel analysis) categories. Studies using control group or intervention data were evaluated first. Secondly, the contributions of time-series and cross-sectional studies were incorporated as policy based evidence. To represent trends across datasets we calculated the percentage reporting a significant relationship between alcohol availability and violence within each dataset category.

2.3 Results

2.3.1 Study selections

Eighty-seven studies met the inclusion criteria, representing analyses of 12 price/tax, 19 trading hour, and 56 outlet density alcohol policy effects on violent crimes/injuries. The majority of studies were conducted in the United States (60%) and Australia (17%). For a complete list of countries see Table 2.1. Twenty-one of the 70 geospatial studies included maps. Ten authors represented their study area, 14 mapped

violent offence rates/counts, 10 depicted the spatial distribution of alcohol outlets, and two mapped their coefficient results (Norström & Skog 2003; Norström & Skog 2005; Livingston 2008; Grubestic & Pridemore 2011; Gruenewald & Remer 2006; Lipton & Gruenewald 2002; Mair et al. 2013; Pridemore & Grubestic 2012a; Britt et al. 2005; Reid et al. 2003; Liang & Chikritzhs 2011; Yu et al. 2010; Scribner et al. 1999; Zhang et al. 2015; Crandall et al. 2015; Jennings et al. 2013; Conrow et al. 2015; Snowden & Pridemore 2013a; Ratcliffe 2012; Burgess & Moffatt 2011; Cameron et al. 2015).

Table 2.1 Count of publications by country of analyses

Country	Alcohol Price or tax	Alcohol Trading Hours	Alcohol Outlet Density	Total
United States	7	1	44	52
Australia	0	6	9	15
England/Wales	2	4	0	6
Sweden	1	2	0	3
Brazil	0	2	0	2
Norway	0	1	1	2
New Zealand	0	0	2	2
Denmark	1	0	0	1
Finland	1	0	0	1
Scotland	0	1	0	1
Canada	0	1	0	1
Colombia	0	1	0	1

2.3.2 Study designs

Of the 87 studies reviewed, 17 ((alcohol price (n = 1), alcohol trading hours (n = 12), alcohol outlet density (n = 4)) employed quasi-control or comparative crime statistics in their analysis. Control group data consisted of comparative region's crime statistics (alcohol price (n = 1), trading hours (n = 9), and outlet density (n = 2) (Kypri et al. 2011; Miller et al. 2012; Norström & Skog 2003; Norström & Skog 2005; Biderman et al. 2009; Douglas 1998; I. Rossow & Norström 2012; Kypri et al. 2014; Humphreys et al. 2013; Zhang et al. 2015)), establishments not adopting an alcohol policy change (Chikritzhs & Stockwell 2002), non-alcohol related crime statistics (Sánchez et al. 2011), alcohol outlets (Humphreys & Eisner 2014) and random locations (Ratcliffe 2012;

Burgess & Moffatt 2011). Twenty three studies conducted intervention analysis where crime data were analyzed pre and post a change in alcohol price/tax (n = 4, 33%), alcohol trading hours (n = 16, 84%), or alcohol licenses (n = 3, 5%). Proportionately cross-sectional datasets were the dominant across the literature (53%), with panel (18%), intervention time-series (16%), intervention panel (10%) and time-series (2%) following. Alcohol price/tax policy changes were most often assessed using panel datasets (50%), alcohol trading hours by intervention time series assessments (76%), and alcohol outlet density studies by cross-sectional datasets (77%).

2.3.3 Violent crime data

The sources of violent crime information and types of crimes studied are summarized in Table 2.2 & Table 2.3. Police reports (n = 61, 70%) and assaults (n = 33, 38%) were the prominent data source and violent event type. Two alcohol price studies used crime data flagged as alcohol-attributable (Matthews et al. 2006; Markowitz et al. 2012). Thirteen alcohol trading hour studies stratified crime data to primary drinking days/hours. Other trading hour studies related violent crime data to alcohol by collecting criminal event data in and around establishments (Chikritzhs & Stockwell 2007; Mazerolle et al. 2012) or relating crime and consumption data through survey information. Whereas, three of the 56 alcohol density studies restricted crime data to peak drinking hours (Livingston 2008; Breen et al. 2011; Ratcliffe 2012) or weekend offences (Breen et al. 2011) to infer alcohol-attributable offences. While others used alcohol-attributable crime from police (Burgess & Moffatt 2011) or conducted analysis of crime around alcohol outlets (Conrow et al. 2015; Ratcliffe 2012; Burgess & Moffatt 2011).

Table 2.2 Source of violent crime statistics

	Source of Crime Information				
	Police Reports	Hospital Admission Records	Survey	State Records	Health Statistics
Alcohol Price or Tax	3	2	4	1	2
Alcohol Trading Hours	15	4	0	0	0
Alcohol Outlet Density	43	9	4	0	0
Total	61	15	8	1	2

Table 2.3 Types of violent crimes/injuries studied

	Violent Crime/Injury Type					
	Assaults	Aggregated Violent Crime	Domestic Violence	Homicides	Child Abuse	Injury caused by violent offence
Alcohol Price or tax	5	0	1	3	1	2
Alcohol Trading Hours	11	3	2	3	0	0
Alcohol Outlet Density	17	26	8	2	2	1
Total	33	29	11	8	3	3

2.3.4 Methodologies

Summarizing the 70 spatial studies we determined that a variety of delineated units were used to represent how violent crime rates were related to alcohol access. Census tracts (n = 17) and zip/postal codes (n = 10) were the most commonly applied geographic units; for a full list see Table 2.4. A large proportion of the total 87 studies (n = 78) used regression modelling techniques to analyze the extent to which alcohol availability is associated with violent crime (price (n = 12), trading hour (n = 14), alcohol density (n = 54). Of these studies, 74 included controls for concurrent policy changes, area, and/or individual characteristics to recognize independent effects, exclusive of alcohol, on violent offence rates. Specifically, 19 considered the concurrent alcohol consumption characteristics, alcohol availability laws, and changes in police force densities on the occurrence of violent incidences.

Table 2.4 Studies categorized by applied spatial units

Spatial Unit	Studies	Count
Census tracts	(Franklin et al. 2010; Freisthler 2004; Gorman et al. 2005; Gyimah-brempong 2001; Reid et al. 2003; Yu et al. 2009; Yu et al. 2010; Zhu et al. 2004; Resko et al. 2010; Scribner et al. 1999; Waller & Iritani 2012; Waller et al. 2012; Wheeler & Waller 2008; Crandall et al. 2015; Jennings et al. 2013; Cameron et al. 2015; Amie L. Nielsen et al. 2005)	17
Zip/postal codes	(Cunradi et al. 2012; Gruenewald et al. 2006; Gruenewald & Remer 2006; Lipton & Gruenewald 2002; Livingston 2008; Livingston 2010; Michael Livingston 2011; M. Livingston 2011; Mair et al. 2013; Freisthler & Maguire-Jack 2015)	10
States	(Cook & Durrance 2013; Durrance et al. 2011; Markowitz 2005; Markowitz 2000; Markowitz & Grossman 2000; Markowitz et al. 2012; Son & Topyan 2011)	7
Block groups	(Costanza et al. 2012; Pridemore & Grubestic 2012a; Pridemore & Grubestic 2012b; White et al. 2015; Snowden & Pridemore 2013a; Snowden & Pridemore 2013b)	6
Census blocks	(Gorman et al. 2001; Grubestic & Pridemore 2011; Speer et al. 1998; Zhang et al. 2015; Morrison et al. 2015)	5
Cities	(E. Vingilis et al. 2008; Parker et al. 2011; Scribner et al. 1995; I. Rossow & Norström 2012)	4
Point level	(Conrow et al. 2015; Ratcliffe 2012; Burgess & Moffatt 2011)	3
Municipalities	(Biderman et al. 2009; Gorman, Labouvie, et al. 1998; Gorman, Speer, et al. 1998)	3
Countries	(Norström & Skog 2003; Norström & Skog 2005)	2
Economic regions	(Matthews et al. 2006; Sivarajasingam et al. 2006)	2
Local government areas	(Liang & Chikritzhs 2011; Stevenson et al. 1999)	2
Police defined areas	(Cunradi et al. 2011; Day et al. 2012)	2
Neighbourhoods	(Britt et al. 2005; T. L. Toomey et al. 2012)	2
Rural Communities	(Breen et al. 2011)	1
Metropolitan areas	(Herttua et al. 2008)	1
Counties	(Schofield & Denson 2013)	1
Buffered college areas	(Scribner et al. 2010)	1
Electoral wards	(Humphreys & Eisner 2014)	1
Total geospatial studies		70

The majority of alcohol price studies (n= 10, 83%) employed linear regression modelling. In the case of an intervention analysis, Autoregressive Integrated Moving Average (ARIMA) (n = 2) or linear models, with a dummy variable were used to understand the effects of alcohol price changes on violent crime rates (Bloomfield et al. 2009; Gustafsson & Ramstedt 2011; Herttua et al. 2008; Cook & Durrance 2013). Alcohol trading hours studies (n = 19) most often employed interrupted time series analysis either through linear regression (n = 4), generalized linear models (n = 5), or ARIMA models (n = 5). To a lesser extent, descriptive analysis (Douglas 1998), distribution comparisons (El-Maaytah et al. 2008; Graham et al. 1998), time-series structural model (Menéndez et al. 2015) or spatial lag regression model (Humphreys & Eisner 2014) were employed. Poisson and Negative Binomial regression models were the dominant methods of estimating the effect of regional alcohol outlet density (n = 17, 30%) on interpersonal violence, only two studies used methods other than regression to study the association between alcohol access and violent offences (Grubestic & Pridemore 2011; Conrow et al. 2015).

To ensure data independence between spatial units, one of the eight cross-sectional alcohol price studies accounted for unit dependence (Markowitz et al. 2012), and 32 of the 56 alcohol outlet density studies controlled or tested for lag 1 (first-order contiguity) autocorrelations, or specified spatially lagged dependency effects between analysis units. One intervention panel (Norström & Skog 2005) and four intervention time-series studies (Chikritzhs & Stockwell 2002; Miller et al. 2012; Menéndez et al. 2015; Humphreys et al. 2013) tested for serial temporal autocorrelation or difference time-series to stationarity, while two intervention panel (Cook & Durrance 2013; Biderman et al. 2009), one panel (Son & Topyan 2011), and one time-series study (Sánchez et al. 2011) explored temporally lagged effects including alcohol consumption or alcohol policy laws on the occurrence of reported violence.

2.4 Policy results

2.4.1 Alcohol price and violent crime

Of the 12 alcohol price or tax policy studies, seven (58%) reported significant policy effects on violent crime and injuries (Cook & Durrance 2013; Markowitz et al. 2012; Markowitz 2005; Matthews et al. 2006; Sivarajasingam et al. 2006; Markowitz & Grossman 2000; Markowitz 2000). One of the four policy intervention studies reported a decrease in assaults and robberies following a 1991 increase in alcohol taxes (Cook & Durrance 2013). Of the six panel studies, four documented a significant relationship between the price of beer and violent event, finding that increases in price had the ability to reduce violent injury, assault, and the probability of being assaulted (Matthews et al. 2006; Sivarajasingam et al. 2006; Markowitz 2005; Markowitz et al. 2012). Similarly, cross-sectional studies reported that a 1% increase in state level excise beer tax was associated with a 0.33% reduction in child abuse rates (Markowitz & Grossman 2000) and 3.10% to 3.50% reduction in domestic abuse cases (Markowitz 2000). The synthesis was less clear for tax reductions, indicating no significant change in violent crime across Nordic countries (Herttua et al. 2008; Bloomfield et al. 2009; Gustafsson & Ramstedt 2011) and no significant association between alcohol United States tax variances and homicides (Durrance et al. 2011; Son & Topyan 2011).

2.4.2 Alcohol trading hours and violent offences

Out of the 19 alcohol trading hour studies, twelve reported significant policy effects on violent crime rates (63%). Seven of the eleven intervention analyses, using control data (Chikritzhs & Stockwell 2002; I. Rossow & Norström 2012; Sánchez et al. 2011; Biderman et al. 2009; Kypri et al. 2011; Douglas 1998; Kypri et al. 2014) and four of the six intervention studies, without control data, found trading hours to significantly affect violent crime (Mazerolle et al. 2012; El-Maaytah et al. 2008; Duailibi et al. 2007; Menéndez et al. 2015), particularly trading hour extensions leading to increases violent crime. Cross-sectional analysis also found that countries with longer trading hours (up to one hour) had four or more violent or gun-related crimes per 100,000 persons per year (Schofield & Denson 2013). Contrasting significant findings, controlled intervention

studies reported no significant effects on the rates of hospital-reported/police-reported assaults and aggregated violence categories when restricting patrons to re-enter on-premises establishments (Miller et al. 2012), allowing variance in on-premises closing times (i.e., staggered closing) (Humphreys et al. 2013; Humphreys & Eisner 2014), and opening off-premises outlets on Saturday opening (Norström & Skog 2003; Norström & Skog 2005). Panel studies, also found no significant change in assaults after a after a one hour extension in alcohol sales (E. Vingilis et al. 2008) and the implementation of staggered closing times for on-premises drinking establishments (Graham et al. 1998).

2.4.3 Alcohol outlet density and violent offences

Among the 56 studies of alcohol outlet density selected, 52 represented significant outcomes. Most notably, intervention analysis indicated that the number of assaults significantly reduced after outlet licensing surrenders in Los Angeles (Yu et al. 2010; Yu et al. 2009) and a 3.2% reduction in on-premises licenses in Buckhead United States lead to a twice greater decrease in the level of violent crime (~6%) (Zhang et al. 2015). All eleven panel studies (Yu et al. 2009; Yu et al. 2010; Cunradi et al. 2012; Parker et al. 2011; M. Livingston 2011; Scribner et al. 1999; Mair et al. 2013; Gruenewald & Remer 2006; Michael Livingston 2011; Cunradi et al. 2011; Conrow et al. 2015) indicated an increasing trend between alcohol outlet density and the occurrence of violence. Longitudinal analysis also showed that additional outlets increased the number of violent street crimes by one-three events per block group over three years in Norfolk Virginia (White et al. 2015). A positive and significant correlation between alcohol outlet density changes and violent crimes (Norström 2000) including homicides (Parker et al. 2011) were found across the time-series studies covering 22 and 35 years of data. The results of panel and time-series studies were consistently reflected by the 43 cross-sectional studies offering 39 significant positive associations between alcohol density and violent crimes (Breen et al. 2011; Britt et al. 2005; Costanza et al. 2012; Day et al. 2012; Franklin et al. 2010; Freisthler 2004; Gorman et al. 2001; Gorman et al. 2005; Grubestic & Pridemore 2011; Gruenewald et al. 2006; Gyimah-brempong 2001; Liang & Chikritzhs 2011; Lipton & Gruenewald 2002; Livingston 2008; Livingston 2010; McKinney et al. 2009; Amie L. Nielsen et al. 2005; Nielsen & Martinez 2006; Pridemore & Grubestic 2012a; Pridemore

& Grubestic 2012b; Reid et al. 2003; Resko et al. 2010; Scribner et al. 2010; Scribner et al. 1995; Speer et al. 1998; Stevenson et al. 1999; T. L. Toomey et al. 2012; Waller & Iritani 2012; Wheeler & Waller 2008; White et al. 2015; Zhu et al. 2004; Crandall et al. 2015; Jennings et al. 2013; Morrison et al. 2015; Snowden & Pridemore 2013b; Snowden & Pridemore 2013a; Ratcliffe 2012; Burgess & Moffatt 2011; Cameron et al. 2015). Only four studies reported inconclusive results (insignificant coefficients) when relating domestic abuse (Gorman, Labouvie, et al. 1998; Waller et al. 2012), child abuse (Freisthler & Maguire-Jack 2015) and assault (Gorman, Speer, et al. 1998) incidences to alcohol outlet densities across municipalities, zip codes, and census tracts.

2.5 Discussion

2.5.1 Policy synthesis

Our literature search identified 87 relevant studies on alcohol access and violent offences conducted across 12 countries, though the majority of analysis was completed in the United States ($n = 52$). Seventy-one studies (82%) reported a significant relationship between alcohol access and violent offences. Alcohol outlet studies represented the greatest percentage of significant results (93%), with trading hours (63%), and alcohol price following (58%). Relationships between alcohol policy and violent offences were reported across all study designs including policy intervention studies using control data to cross-sectional overviews (Table 2.5).

Table 2.5 Summary results of the selected publications. Presented are the percent of studies reporting significant/substantive policy effects on violent injury/crime categorized by study design, policy type, and combined policy types.

	Percent of Significant/Substantive Findings				
	Intervention time-series	Intervention Panel	Panel	Cross-sectional	Time-series
Alcohol Price or Tax	0%	50%	67%	100%	N/A
Alcohol Trading Hours	66%	25%	100%	100%	100%
Alcohol Outlet Density	N/A	100%	100%	91%	100%
Number significant	8	5	14	42	2

Consistent trends emerged across the alcohol availability policies. Using cross-section, panel, and intervention research designs, with various levels of data aggregation, researchers identified that alcohol tax and price increases significantly reduce violent offences including: child abuse, intimate partner violence, assaults, and injuries (Markowitz 2000; Markowitz & Grossman 2000; Markowitz 2005; Markowitz et al. 2012; Matthews et al. 2006; Sivarajasingam et al. 2006). Particularly when price increases were directed towards commonly consumed alcohol such as beer. Effects were independent of regional and individual's socio-economic and demographic characteristics and consistent when monitoring the change in the number of emergency room attendees for alcohol-related violence (Matthews et al. 2006).

Overviewing both intervention and time-series studies results, substantive trading hour restrictions (e.g., 24hr access changed to regulated closing hours or more than 2 hour restriction in on-premises alcohol sales hours) led to marked reductions in homicides, battery, domestic violence and assaults (Biderman et al. 2009; Duailibi et al. 2007; Kypri et al. 2011; Douglas 1998; Kypri et al. 2014; Menéndez et al. 2015). At on-premises locations, staggered closing times reduced regional rates of violent offences by 34% (El-Maaytah et al. 2008) and restricting re-entry reduced 50% of offences occurring on-premises (Mazerolle et al. 2012). The effects of trading hour restrictions were also consistent for alcohol-attributable assault injuries (El-Maaytah et al. 2008). Symmetrically, the extension of trading hours, up to one hour, increased assaults (Chikritzhs & Stockwell 2002; I. Rossow & Norström 2012; Biderman et al. 2009) and homicide rates (Sánchez et al. 2011).

Consistently intervention, time-series, panel and cross-section studies found that increases in spatial density of alcohol outlets led to higher rates violent crimes, with the effects magnified in marginalized communities (Zhu et al. 2004; Yu et al. 2009; T. L. Toomey et al. 2012; Britt et al. 2005; Stevenson et al. 1999; Scribner et al. 2010; Scribner et al. 1995; Reid et al. 2003; Nielsen & Martinez 2006; Gyimah-brempong 2001; Gorman et al. 2005; Gorman et al. 2001; Costanza et al. 2012; Breen et al. 2011; White et al. 2015; Franklin et al. 2010; Jennings et al. 2013; Snowden & Pridemore 2013b; Snowden & Pridemore 2013a; Crandall et al. 2015; Amie L. Nielsen et al. 2005). A strong positive and significant association between on-premises license densities and assaults were

observed by multiple researchers (Lipton & Gruenewald 2002; Gruenewald et al. 2006; Liang & Chikritzhs 2011), with local-level analysis clearly showing clusters of assaults, violent crime, and violent crime flagged as alcohol-attributable (e.g., (Burgess & Moffatt 2011)) around alcohol outlets (Pridemore & Grubestic 2012b; White et al. 2015; Conrow et al. 2015; Ratcliffe 2012; Burgess & Moffatt 2011). Exponential increases in violent crime were observed in postal code regions with greater than 25 establishments (McKinney et al. 2009; Livingston 2008). Separating outlet effects by licensing type, numerous studies found higher amount of violent offences around a greater amount of bars or on-premises licenses (excluding restaurants) (Lipton & Gruenewald 2002; Gruenewald et al. 2006; Cunradi et al. 2012; Pridemore & Grubestic 2012a; Ratcliffe 2012; Snowden & Pridemore 2013b; Conrow et al. 2015; Crandall et al. 2015; Zhang et al. 2015; Cameron et al. 2015) with the effects of bars doubling violent offences in economically deprived areas (Gruenewald et al. 2006). In rural settings, the same increase in regional violent offences rates were seen with a higher densities of off-premises outlets (Stevenson et al. 1999). A greater density of off-premises licenses were also related to a greater amount of gunshot wounds (Crandall et al. 2015) and intentional injuries (Morrison et al. 2015) in regions of the United States and Australia.

Generally, increased access led to higher rates of violent crime with drinking establishments acting as hot spots of violent crime, though a smaller percentage of studies (18%) reported insignificant effects (alcohol price (42%), alcohol trading hours (37%), and alcohol outlet density (7%)). Researchers relating homicides to variances in state-wide alcohol tax rates were unable to identify significant associations (Durrance et al. 2011; Son & Topyan 2011). The power of analysis was questioned by the low variability in tax rates across states by the authors (Durrance et al. 2011), and we caution against relating state wide policy to individual crime events, though intervention or individual data are needed to properly assess the effects of alcohol tax on heinous crimes.

We also found asymmetry between the influences of tax increases and reductions. Tax increases (Markowitz & Grossman 2000; Cook & Durrance 2013) led to significant reductions in violent crimes while tax reductions had no significant effects on violent crime in other regions (Gustafsson & Ramstedt 2011; Bloomfield et al. 2009; Herttua et al. 2008). Possibly population characteristics (Nordic countries verses United

States) or differences in methodologies (panel verses intervention) were dictating the asymmetric pattern, though further analysis is needed to report the general effect of tax reductions on violent crime, particularly considering how tax affects real price indexing for consumers.

A few trading hour policies reported no significant reduction in violent crime (E. Vingilis et al. 2008), namely after the opening of off-premises locations on Saturdays (Norström & Skog 2003; Norström & Skog 2005), restricting patron re-entry (Miller et al. 2012), and staggering closing times of on-premises locations (Graham et al. 1998; Humphreys et al. 2013; Humphreys & Eisner 2014). It is likely that the marginal effects on crime were caused by people planning for regulated closures of off-premises outlets (Norström & Skog 2003; Norström & Skog 2005). And while modest re-entry restrictions and staggered closings did not create substantive reductions crime rates in some regions, the peaks in the spatial and temporal patterns of alcohol-attributable crime were effected (Graham et al. 1998; Mazerolle et al. 2012; Kypri et al. 2011; E. Vingilis et al. 2008; Humphreys et al. 2013). Policies that dictate the spatio-temporal pattern of crime are essential for proactive policing, though a larger number of local studies are needed to document consistency of the effect.

In terms of alcohol outlets, a minority of studies reported insignificant effects (Gorman, Labouvie, et al. 1998; Gorman, Speer, et al. 1998; Waller et al. 2012; Freisthler & Maguire-Jack 2015). Some uncertainty remains regarding the effects of on verses off premises alcohol establishments on domestic violence (e.g., (Cunradi et al. 2011; Cunradi et al. 2012)). Spatial scale of alcohol access measurement (municipalities/zip codes) and consumption data (e.g., (Waller et al. 2012)) may have masked effects of outlets on violent crime though a greater amount of data collected on “ the place of intoxication” is needed to make conclusive results regarding domestic violence and the types of alcohol outlets. Preliminary studies, indicate that individuals drinking in pubs, taverns, hotels and bars increased the likelihood of domestic violence (Livingston 2010) and child maltreatment (Freisthler 2004); however, alcohol consumption rather than place may be influencing domestic altercations. Survey respondent data are needed to confirm results.

2.5.2 Study design considerations

Overall, consistent policy trends were identified among a vast heterogeneity of study designs, outcome measures, and statistical models. Unfortunately, an insufficient amount of intervention ($n = 23$) or control (e.g., comparative region or point crime statistics) ($n = 15$) studies exist. Twenty-six percent of the studies explored the change in violent crime post an alcohol-policy intervention, the remaining 74% conducted panel, time-series, or cross-sectional assessments studying trends in the variances of alcohol access and crime. There are ways to tease out causality in a plethora of observation, mostly ecological (aggregated unit) studies. For example, a greater number of researchers could consider the concurrent implications of independent alcohol policies and active policing on the occurrences of violent crime or reporting. Currently, only 32% of studies have considered the simultaneous effects of alcohol policies (Markowitz & Grossman 2000; Markowitz 2000; Cook & Durrance 2013; Graham et al. 1998; Breen et al. 2011; McKinney et al. 2009; Waller et al. 2012; Waller & Iritani 2012; Liang & Chikritzhs 2011; Resko et al. 2010) including: quota abolishment on alcohol sales (Bloomfield et al. 2009; Gustafsson & Ramstedt 2011; Norström & Skog 2003), outlet densities (Markowitz 2005; Schofield & Denson 2013; Markowitz & Grossman 2000; Markowitz 2000), dry laws (Markowitz 2005; Markowitz & Grossman 2000), or changes in police force capacity (Markowitz 2005; Biderman et al. 2009; Chikritzhs & Stockwell 2002; Duailibi et al. 2007; Breen et al. 2011); however, these independent factors play a pivotal role in the estimation of violent crime.

To enhance the reliability of estimation effects garnered from cross-sectional or panel studies with limited longitudinal data, future studies could implement a cross-validation or “hold back” method of model validation where a proportion of the dataset is used to build the alcohol availability-violence model and a portion of data are withheld to use as validation for model predictions. Currently, only two studies validate the efficiency and transferability of their model using test data (Wheeler & Waller 2008; Parker et al. 2011). It is equally important to address statistical assumptions of regression models prominently used across the literature. We found that across the geo-spatial studies ($n = 70$) 32 tested for spatial dependence and four (Norström & Skog 2005; Chikritzhs & Stockwell 2002; Miller et al. 2012; Humphreys et al. 2013; Menéndez et al.

2015) of the time-series studies tested for temporal serial autocorrelations. Untested datasets are vulnerable to autocorrelation which can result in clustered residuals and artificial decreases in the standard errors (Anselin 1989; Cliff & Ord 1981).

We caution against studies attributing survey respondent crime information to geographic measurements of alcohol access (e.g., state-wide alcohol taxes or postal code level outlet densities) to infer causation. Using ecological characteristics to understand behaviours of individuals can lead to fallacies of inference from unmatched scales (Piantadosi et al. 1988) as does generalizing individual results to a group. Studies that use generalized measures of alcohol policies without control groups, or intervention analysis, are vulnerable to falsely attributing violent crime rates to alcohol access policy. Therefore, to limit the potential biases, study designs, whenever possible, should compare response and predictor data between comparable scales, over time, or subsequent to a policy change. Results should be compared between study designs and across scales when synthesizing information from study designs attributing individual responses to environmental factors in the individual's area.

In terms of data, there are opportunities to record alcohol use indicators and place of last consumption to develop joint distributions between crime and alcohol use, though the majority ($n = 59$) of crime datasets were not linked to intoxication or place of consumption. We recognize that confining studies to alcohol-attributable data would present a limited scope with primary data sources including surveys ($n = 8$), and generalized police reports ($n = 61$). However, hospital admissions data collection ($n = 15$) presents the opportunities to collect consumption information (i.e., blood alcohol level) and wherever possible we suggest studies use crime data collected at detailed spatial or temporal scales to strengthen causality. These may include geo-located crimes in or around alcohol establishments, crimes occurring during on-premises closing times, or crimes recorded between peak drinking hours (Room et al. 2012). Authors have recognized the benefits of stratifying crime reports to strengthen model or analysis results (Chikritzhs & Stockwell 2007; Mazerolle et al. 2012; Livingston 2008; Breen et al. 2011; Ratcliffe 2012; Burgess & Moffatt 2011; Humphreys & Eisner 2014; Humphreys et al. 2013). Such that, crimes occurring outside of drinking hours, that may have a different spatial or temporal distribution, do not mask the relationship between alcohol access

policies and violent crime especially in the absence of intervention analysis where it is plausible to attribute changes in the occurrence of crime to the change in alcohol policy.

Considering exploratory data, a substantial portion (68%, $n = 38$) of the alcohol density studies assessed the relative impact of on-premises versus off-premises outlets, 18 studies analyzed the aggregated effects of alcohol outlet densities reducing the usefulness for setting outlet density restrictions by type. We suggest studies continue to undertake comparative analysis between types of outlet establishments and seek to collect sales data in which, for instance, establishments of different size and capacity are not measured equally in the model. Currently, the results between on- and off-premises alcohol outlet density and violent outcomes measures are variable for some violence types and standardization of outlet grouping and sensitivity analyses on the co-linearity between outlet density types is essential to consolidate results.

2.5.3 Geographic perspective for future research

The majority of alcohol availability studies used a spatial unit (e.g., states, cities, census tracts, neighbourhoods, blocks) to associate the count or rates of offences against regionally specific socio-demographic and alcohol policy variances, such as changes in price (Cook & Durrance 2013; Herttua et al. 2008; Matthews et al. 2006), hours of closing (Schofield & Denson 2013; Biderman et al. 2009), or alcohol outlet densities (White et al. 2015; Wheeler & Waller 2008; Costanza et al. 2012; Grubestic & Pridemore 2011). Census tracts and zip code areas were the dominant analysis (39%), with few studies conducted at units smaller than a census tract (Costanza et al. 2012; Pridemore & Grubestic 2012a; Pridemore & Grubestic 2012b; White et al. 2015; Snowden & Pridemore 2013a; Snowden & Pridemore 2013b; Conrow et al. 2015; Ratcliffe 2012; Burgess & Moffatt 2011; Gorman et al. 2001; Grubestic & Pridemore 2011; Speer et al. 1998; Zhang et al. 2015; Morrison et al. 2015; Britt et al. 2005; T. L. Toomey et al. 2012). As a result, available information for evidence-based policy making is focused on expected effects of broad scale (e.g., state wide or city wide) policy changes to alcohol tax, trading hours, or outlet densities. More information from local-level or event level analysis is needed to understand if targeting alcohol availability restrictions toward problem venues or specific neighbourhoods would have the same or greater net effect on violent crime reduction. For

example, establishment licensing decisions are often made considering neighbouring crime rates and outlets within 500m radius, though very few results are presented at matching scales (Conrow et al. 2015; Ratcliffe 2012; Burgess & Moffatt 2011). We recognize that standardizing crime rates becomes particularly hard at the local level when persons move between analysis units (e.g., blocks). However, using crowd sourced population estimates from social media (Malleon & Andresen 2014) or remotely sensed data of night time lights (Dobson et al. 2000) can offer new ways of quantifying dynamic (changing) populations estimates at smaller units than the most common postal codes or census tracts. For example, researchers can use geo-located (i.e., x,y coordinates) social media status updates (e.g., tweets), searched using open source software such as `twitterR` (<https://cran.r-project.org/web/packages/twitterR/index.html>), as a proxy for the spatio-temporal location of sub populations and their sentiments (e.g., (Malleon & Andresen 2014)). Twitter data has proven to improve the prediction of various crime types (Gerber 2014). It is also possible to redistribute population estimates from larger census units using indicators of land use (night-time) lights and other attributes (e.g., land slope) to estimate where the residential population spends the majority of their time on the landscape (e.g., LandScan data), creating population estimates as fine as 1km spatial resolution (Dobson et al. 2000).

Many researchers have also focused on reporting results as an effect size, such that a unit increase in alcohol price, hours of trading, or rate of establishments creates a percentage increase in violent offences across study areas. While vital for policy-based evidence, the spatial interpretation of the alcohol-violence relationship is lost. Understanding where populations are most vulnerable to alcohol access is useful for local policy making, such as choosing restrictions on alcohol outlet locations, targeting trading hour restrictions to specific problem areas, or implementing minimum prices at problem venues. Mapping is shown to aid in monitoring the statistical assumption such as residual patterns (Morrison et al. 2012), interpreting, and communicating policy results (Crombie et al. 2007; Babor et al. 2010) though only 21 of the 70 spatial analyses included maps (Norström & Skog 2003; Norström & Skog 2005; Livingston 2008; Grubestic & Pridemore 2011; Gruenewald & Remer 2006; Lipton & Gruenewald 2002; Mair et al. 2013; Pridemore & Grubestic 2012a; Britt et al. 2005; Reid et al. 2003; Liang &

Chikritzhs 2011; Yu et al. 2010; Scribner et al. 1999; Jennings et al. 2013) of which two were limited to a depiction of study area (Norström & Skog 2003; Norström & Skog 2005). Therefore, opportunities for enhancing spatial representation are available.

With the size of analysis units decreasing with the advent of Geographical Information Systems opportunities are presented to study the spatially lagged effects of alcohol availability on neighbouring crime rates or apply spatial modelling techniques (Geographically Weighted Regression) to address heterogeneity of alcohol-crime relationships over board spatial areas (e.g., (Cameron et al. 2015)). Currently, 25 (Markowitz et al. 2012; Yu et al. 2009; Cunradi et al. 2011; M. Livingston 2011; Mair et al. 2013; Gruenewald & Remer 2006; Breen et al. 2011; Costanza et al. 2012; Franklin et al. 2010; Gorman et al. 2001; Gorman et al. 2005; Grubestic & Pridemore 2011; Gruenewald et al. 2006; Lipton & Gruenewald 2002; Livingston 2008; Livingston 2010; Amie L. Nielsen et al. 2005; Nielsen & Martinez 2006; Pridemore & Grubestic 2012a; Stevenson et al. 1999; White et al. 2015; Zhu et al. 2004; Morrison et al. 2015; Snowden & Pridemore 2013b; Snowden & Pridemore 2013a) studies incorporated spatial lagged effects of which the majority considered the effects of alcohol access in neighbouring units, though it is possible to study multiple lagged effects to understand the distance decay or alcohol accessibility changes on violent occurrences to create evidence based policies for establishment hours and densities. For example, Pridemore and Grubestic (Grubestic & Pridemore 2011) used spatial cluster detection and autocorrelation analysis to identify where, at what density, and to what extent assaults were clustering around different types of establishments and three other point analysis studies (Conrow et al. 2015; Ratcliffe 2012; Burgess & Moffatt 2011) used multiple analysis buffers around individual establishments to indicate the extent at which crime clusters around particular outlets. However, more studies applying smaller spatial units should consider distance effects to make conclusive recommendations for the allowable proximity of establishments or density of establishments in neighbouring units.

Using geo-located event crime data, we can use point pattern analysis to study relationships between alcohol and crime. Currently, almost all (97%) of the alcohol policy studies reviewed have conducted aspatial analysis or modelling using contiguous analysis units. Point patterns assessments can provide information on how crime clusters

around establishments (Burgess & Moffatt 2011; Ratcliffe 2012), during various drinking hours (Conrow et al. 2015), and pricing schemes for preventative planning at specific sites. Recent publications using point data and density mapping have been shown to provide great insight into the influences of different drinking environments (Walker et al. 2012) though to capitalize on these methods future analysis needs to shift from regression based modelling to spatio-temporal point pattern analysis perspective (see (Diggle 2013)).

2.5.4 Conclusion

Repeatedly findings showed that targeting the price of commonly consumed alcohol (e.g., beer), restricting the days of sales, and limiting the clustering of alcohol establishments can have protective effects for violence perpetration. Summarizing 87 studies, representing 12 alcohol price changes, 19 trading hour/days modifications, and 56 alcohol outlet density studies we found a lack of control or intervention study designs leaving policy personnel to rely heavily on the results from cross-sectional analyses. What remains unclear are the effects of tax reductions, the effectiveness of moderate trading policies (lock-out), and the varying effects of establishment types on violence. We believe cross-sectional studies could improve in quality by holding data back to conduct validation tests on their models, more commonly consider the concurrent effects of alcohol policies and law enforcement on crime reporting, and conduct analysis across smaller spatial units providing visualization of crime and alcohol access over time and space for decision making. In terms of data, researchers should capitalize on opportunities to collect the joint distribution of crime occurrences and intoxication in plausible cases such as during hospital admissions. Further, we believe that there is a greater opportunity to access the variable effect of establishment types on crime by disaggregating licensing types and control for any collinearity between density measurements within the analysis. Despite methodological limitations and some variable findings, it is essential to remember that well designed studies have indicated that even modest policy changes including a 1% increases in alcohol price, one hour changes in closing times, or limitations on establishment densities to less than 25 outlets can lead to substantive reductions in violent crime/injury occurrences. Recognizing the diversity of

datasets, levels of aggregation, and methods the majority of studies indicated that increasing the price, limiting the hours of sales, and restricting the number of establishments are effective policies for alcohol-attributable violent injury/crime management.

3 Chapter 3

A review of the statistical and quantitative methods used to study alcohol-attributable crime

Abstract

Modelling the relationship between alcohol consumption and crime generates new knowledge for crime prevention strategies. Advances in data, particularly data with spatial and temporal attributes, have led to a growing suite of applied methods for modelling. In support of alcohol and crime researchers we synthesized and critiqued existing methods of spatially and quantitatively modelling the effects of alcohol exposure on crime to aid method selection, and identify new opportunities for analysis strategies. We searched the alcohol-crime literature from 1950 to January 2014. Analyses that statistically evaluated or mapped the association between alcohol and crime were included. For modelling purposes, crime data were most often derived from generalized police reports, aggregated to large spatial units such as census tracts or postal codes, and standardized by residential population data. Sixty-eight of the 90 selected studies included geospatial data of which 48 used cross-sectional datasets. Regression was the prominent modelling choice ($n = 78$) though dependent on data many variations existed. There are opportunities to improve information for alcohol-attributable crime prevention by using alternative population data to standardize crime rates, sourcing crime information from non-traditional platforms (social media), increasing the number of panel studies, and conducting analysis at the local level (neighbourhood, block, or point). Due to the spatio-temporal advances in crime data, we expect a continued uptake of flexible Bayesian hierarchical modelling, a greater inclusion of spatial-temporal point pattern analysis, and shift toward prospective (forecast) modelling over small areas (e.g., blocks).

3.1 Introduction

Alcohol supply restrictions continue to relax across the globe, leading to increases in disease (Rehm et al. 2010; Babor et al. 2010), dependency (Plant et al. 2000), injury (Watt et al. 2004; Stockwell et al. 2002), and crime (Resko et al. 2010; Gorman et al. 2005; Parker et al. 2011; Nielsen & Martinez 2006; Liang & Chikritzhs 2011; Livingston 2008). Of particular concern, is the large proportion (~30%) of criminal offences committed while intoxicated (Pernanen et al. 2002; Felson & Staff 2010; Mumola 1999; Myrskog 2012). For instance, researchers continue to demonstrate that, independent of socio-economic and demographic influences, higher alcohol access leads to greater rates of crime, including violent offences (Gruenewald et al. 2006; Lipton & Gruenewald 2002; Mazerolle et al. 2012), disturbance (Kypri et al. 2008), property damage (Wilkinson & Livingston 2012), and drunk driving (Gruenewald et al. 2002).

Modelling the relationship between alcohol consumption and crime can enable the coordination of preventative police patrolling and alcohol access restrictions. As such, health researchers are tasked with understanding how populations will respond to alcohol access and promotion (Campbell et al. 2009). Main questions include: how the change and distribution of alcohol price (Cook & Durrance 2013; Markowitz et al. 2012; Matthews et al. 2006), hours of sales (Chikritzhs & Stockwell 2002; Evelyn Vingilis et al. 2008; Ingeborg Rossow & Norström 2012), establishment types (Liang & Chikritzhs 2011; Waller et al. 2012; Yu et al. 2010; Mair et al. 2013; T. L. Toomey et al. 2012), or consumption patterns (Gruenewald et al. 2002; Treno et al. 2003) influence the rate of criminal offences. To accurately estimate alcohol consumption and alcohol policy effects on crime, data quality and selection of appropriate statistical methods are integral.

Advances in Global Positioning Systems (GPS) and Geographical Information Systems (GIS) studies are increasing the use of detailed spatial units for alcohol-crime modelling (e.g., neighbourhoods, blocks, (Gorman et al. 2001; T. L. Toomey et al. 2012; Wheeler & Waller 2008; Grubestic et al. 2012)) and results from longer times-series (ten years plus) are becoming available (e.g., (Ingeborg Rossow & Norström 2012)). With data increasing in spatial and temporal detail the likelihood of dependency between analysis units and time periods increases. If not explicitly addressed, autocorrelation

(positive correlation of data between regions or time periods) can violate the assumptions of statistical modelling leading to clustered residuals and an artificial decrease in standard errors, such that dependence between data reduces the effective sample size (n) (Anselin 1989; Cliff & Ord 1981). As a result, a growing suite of methods have emerged to model spatial and temporal structure across the crime-alcohol studies.

To date, other reviews have summarized the effects of alcohol exposure on crime (Campbell et al. 2009; Popova et al. 2009; Wagenaar et al. 2010; Stockwell & Chikritzhs 2009; Livingston et al. 2007; Gruenewald 2007), but not the methods used for estimation of the effects. The objective of our study was to evaluate data and the suitability of quantitative analysis strategies to model the effect of alcohol access/consumption on crime abundance by synthesizing current trends and highlighting methods keenly adapted to spatial effects modelling. The review is structured in a manner that first describes the selection of studies reviewed. Secondly, data characteristics, applied spatial units, and dataset structure are summarized. Finally, dominant statistical approaches are reviewed and critiqued, and new opportunities for data measurement and spatial analysis are discussed.

3.2 Study selection and synthesis

We searched the alcohol-crime literature from 1950 to January 2014 using the Web of Science and Google Scholar databases. A list of key terms used singularly and combined with the following Boolean statement: (alcohol consumption OR binge drinking OR heavy drinking OR drinking patterns OR alcohol tax OR alcohol price OR alcohol cost OR alcohol outlet OR alcohol outlet density OR alcohol trading hours OR alcohol sales OR alcohol availability OR alcohol licensing OR on-premises OR off-premises OR bar OR pub OR hotel) AND (crime OR violent crime OR violence OR assaults OR domestic violence OR rape OR homicide OR interpersonal violence OR drinking and driving OR impaired driving OR drunk driving OR disturbance OR nuisance crime OR property crime OR amenity problems). Analyses that quantitatively evaluated or mapped the association between alcohol and crime were included (see Table 3.1 for search term descriptions and Figure 3.1 study selection criteria).

Table 3.1 Search term descriptions

Search Term	General description
Blood alcohol level	Percentage of alcohol contained in a person's blood
Alcohol consumption	Ingestion of alcohol
Binge drinking	Drinking habits that lead to persons blood alcohol concentration to be 0.08grams or above (National Institute on Alcohol Abuse and Alcoholism n.d.)
Heavy drinking	Drinking five or more drinks at the same occasion five days out of thirty (National Institute on Alcohol Abuse and Alcoholism n.d.)
Drinking patterns	The frequency and amount of a person's alcohol consumption
Alcohol tax	Government's financial charge on alcoholic beverages
Alcohol price	The consumer's price including cost and tax for purchasing alcohol
Alcohol cost	The consumer's price before tax for purchasing alcohol
Alcohol outlet	On or off premises alcohol sales establishment
Alcohol outlet density	Measure of alcohol outlets per regional area standardize by population counts, roadways, or area
Alcohol trading hours	Permitted hours for alcohol sales
Alcohol sales	Days permitted to sell alcohol and gross profit received from alcohol sales
Alcohol availability	Population's exposure to alcohol supply
Alcohol licensing	Permit allowing the sale of alcohol
On-premises	Establishment where alcohol consumption occurs within the building
Off-premises	Establishment where alcohol is purchased inside, but consumed outside
Bar	Establishment serving alcoholic drinks, sometimes dancing is an activity
Pub	Establishment serving alcoholic drinks and food
Hotel	Establishment offering housing that also serves alcoholic drinks and food
Crime	An action or omission that may be prosecuted by the government and is punishable by law
Violent	Using physical force to harm someone, a group, or something
Violence	Behaviour using physical force to harm someone, a group, or something
Assault	Physical attack against someone or something
Domestic violence	Violent or aggressive behavior between members of a home, usually between spouses or partners
Rape	Unlawful sexual acts or intercourse, with or without force, without the consent of the victim
Homicide	Deliberate killing of one person by another
Interpersonal violence	One person uses physical, mental, or financial power to control another person
Drinking and driving	Driving a motor vehicle after or during consuming alcohol
Impaired driving	Driving a motor vehicle while intoxicated
Drunk driving	Driving a motor vehicle while intoxicated by alcohol
Disturbance	Interruption of a settled environment
Nuisance crime	Minor crime that constitutes an injury, loss, or damage to a community rather than an individual
Property crime	Theft or destruction of someone's personal belongings without force or threat of force
Amenity problems	Neighbourhood disturbance, litter, or noise

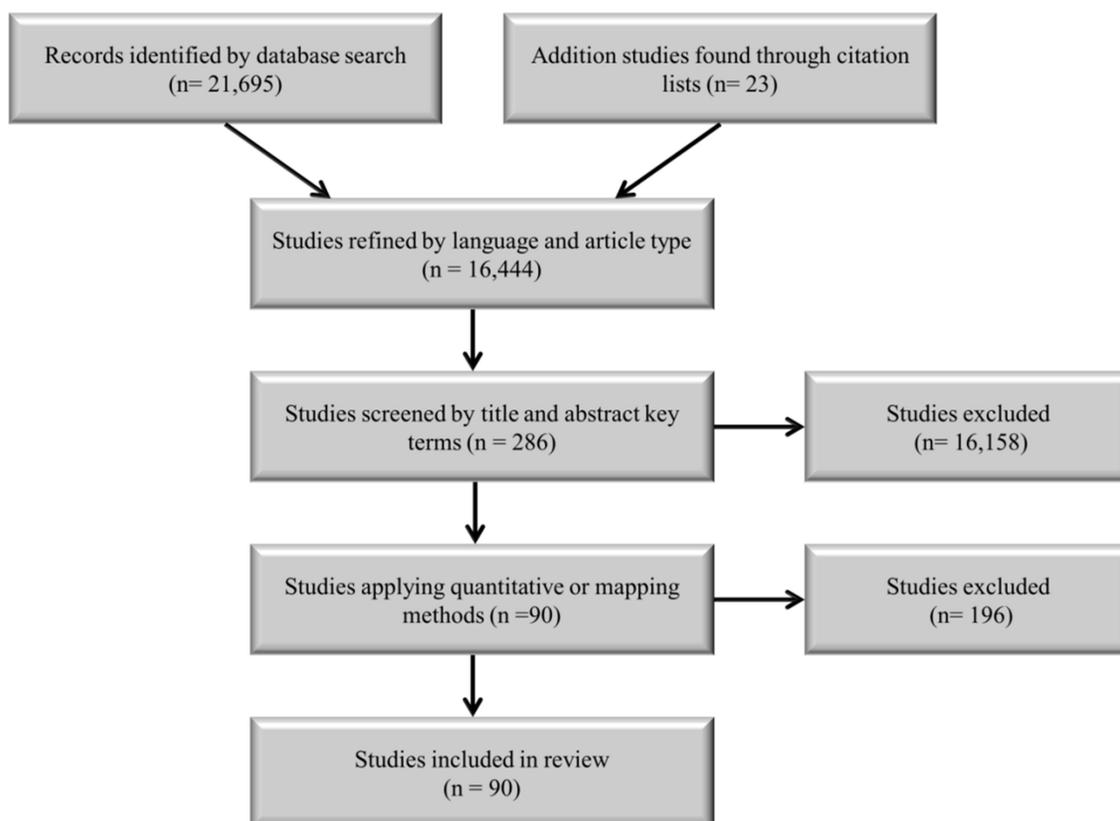


Figure 3.1 Study selection criteria

We calculated the number of countries represented across our sample and addressed if alcohol consumption was measured directly (e.g., blood alcohol level or survey admission of intoxication) or indirectly as measures related to exposure /use (e.g., alcohol price, hours of sales, or establishment access). Additionally, the frequency of different crime types and crime data sources were summarized. Spatial units were recorded and percent change in use before and after 2009 was calculated by subtracting the proportion of studies applying the analysis unit before 2009 from the proportion of studies applying the same unit after 2009. The results indicate an increasing or decreasing trend in unit application through time. Studies were then categorized by dataset structure including: cross-section (individual or regionally aggregated data collected at the same time), time-series (data collected over one region, but multiple time periods), panel (data collected over multiple spatial units and time periods), and intervention data (data indicating a change in alcohol exposure over time). After categorizing studies by

structure, we summarized and critiqued methods used to estimate the effects of alcohol on crime including categories for: Autoregressive Integrated Moving Average (ARIMA) models, generalized linear regression (GLM), hierarchical and non-linear regression modelling (including spatial and temporal modelling), and finally a section for regression trees, spatial and temporal mapping.

3.3 Results

3.3.1 Data

From the selections, 90 studies were included. Of selected studies, 56 were conducted in the United States and 16 in Australia, representing 80% of the sample (Table 3.2). The effects of alcohol consumption on crime were often measured as indicators related to alcohol use (89% of the studies), including: alcohol outlet counts or rates per region (n = 55), on-premises closing times (n = 10), alcohol tax (n = 7), volume of alcohol sold (n = 7), alcohol sales hours (n = 5), distance to alcohol outlets (n = 3), real price of alcohol (n = 3), or sale lock-outs (n = 2). The regional rates of alcohol outlet density exposure were calculated per 100,000 (n = 1), 10,000 (n = 3), 1,000 (n = 9), and 100 (n = 5) persons and as a density per square mile (n = 5) or roadway (n = 8). To a lesser extent, alcohol effects were measured directly from survey respondent consumption habits (n = 7) or blood alcohol levels (n = 3).

Table 3.2 Country study areas

Country	Number of Studies
United States	56
Australia	16
Canada	5
Brazil	3
England	2
Sweden	2
Norway	2
New Zealand	1
Finland	1
Denmark	1
Scotland	1

Crime data included a variety of crime types and sources including aggregated crime categories (n = 8), violent offences (n = 70) drunk driving/crashes (n = 6), or nuisance crimes (n = 6), sourced from police records (n = 57), hospital admissions (n = 16), health statistics (n = 4), or surveys (n = 13). Five studies stratified police recorded data to peak alcohol drinking hours consisting of weekday and weekend evenings to reduce risk of spurious results (Chikritzhs & Stockwell 2007; Breen et al. 2011; Biderman et al. 2009; Treno et al. 2007; Spicer et al. 2012).

3.3.2 Spatial units

Across the 90 studies selected, 68 studies used a spatial unit to measure crime or alcohol exposure. In most cases (n = 57, 83%), both crime and alcohol access data were aggregated to the same analysis unit. The remaining studies measured alcohol access across a larger spatial unit and related the regional alcohol exposure to crime reports associated with individuals. For example, state level alcohol taxes (Markowitz 2005; Markowitz & Grossman 2000), and city (Treno et al. 2003), zip code (Gruenewald et al. 2002; McKinney et al. 2009), neighbourhood (Wilkinson & Livingston 2012; Wechsler et al. 2002), census tract (Iritani et al. 2013; Waller et al. 2012; Waller & Iritani 2012; Resko et al. 2010), campus (Scribner et al. 2010) and police region (Jackson & Owens 2011) alcohol outlet density measures were used to estimate criminal incidences at the individual level.

Overall postal/zip codes (n = 11) and census tracts (n = 16) were the most commonly applied units. Analyzing trends before and after 2009 we found a decline in the use of larger state (-3%), postal code (-9%), city (-6%), municipality (-9%), and economic regions (-6%) and an increase in smaller police (9%), neighbourhood (9%), block (3%), block group (15%), and campus (3%) units (Table 3.3). The smaller unit studies were exclusive to North American.

Table 3.3 Applied analysis units counted by country, overall use before and after 2009, and the percent change in use after 2009. Percent change in use was calculated by subtracting the proportion of studies applying the analysis unit before 2009 from the proportion of studies applying the same unit after 2009.

Spatial Unit	Count Per Country								Overall Summary		
	United States	Australia	Canada	Brazil	United Kingdom	Norway	New Zealand	Finland	Count Before 2009	Count After 2009	% Change
Blocks	2		1						1	2	2.94
Block groups	7								1	6	14.71
Campuses	1								0	1	2.94
Neighbourhoods	5								1	4	8.82
Police Regions	2						1		0	3	8.82
Postal/Zip Codes	7	4							7	4	-8.82
Rural Areas		1							0	1	2.94
Census Tracts	16								9	7	-5.88
Municipalities	2			1					3	0	-8.82
Government Areas		2							1	1	0.00
Economic Regions					2				2	0	-5.88
Counties	2								1	1	0.00
Cities	2	1				1		1	3	2	-2.94
User defined	2								2	0	-5.88
States	5								3	2	-2.94

3.3.3 Dataset structure

Datasets were dominated by cross-sectional assessments ($n = 54$, 60%), eleven of which analyzed individual level crime data. Sixteen studies (18%) used time-series data to assess how alcohol exposure varied with crime across time, 15 of which monitored the change crime incidence after an alcohol policy intervention. Finally, 20 researchers (22%) conducted analyses on panel data to address how alcohol exposure varied with crime over time and space, in which five analyzed an alcohol policy intervention. Overall, the study of panel datasets was a trend of newer publications. Only four panel studies were published before 2009 (Treno et al. 2007; Matthews et al. 2006; Gruenewald & Remer 2006; Sivarajasingam et al. 2006).

3.4 Statistical approaches

3.4.1 Autoregressive integrated moving average

Autoregressive Integrated Moving Average (ARIMA) models were selected for five of the 15 intervention time-series studies modelling the effects of on-premises alcohol establishments changes (Norström 2000), alcohol tax reductions (Bloomfield et al. 2009; Gustafsson & Ramstedt 2011), change in outlet closing (Ingeborg Rossow & Norström 2012), and alcohol sales hours (Norström & Skog 2003) on annual (Norström 2000) and monthly incidence of assaults. Trends in the crime data were specified by three terms of the ARIMA model: the auto-regressive term (characterizes the temporal correlation in the series), the integrated trend (transforms the trend to stationarity), and the moving average (smoothes any random patterns or seasonal effects) (Cheng et al. 2014). Possible shifts in the incidence of crime were monitored using a dichotomous indicator variable (pre (0) and post (1) change).

3.4.2 Generalized Linear Model

A large portion ($n = 37$, 41%) of the reviewed studies used generalized linear models (GLMs) to estimate the incidence of crime (outcome variable) as a function of the alcohol exposure and socio-demographic controls across intervention times-series ($n =$

10), cross-sectional ($n = 23$), panel ($n = 3$), and intervention panel ($n = 1$) datasets. GLMs are an extension of simple linear regression used to model crime as any member of the exponential family of distributions, conditional on the covariates, using a link function (e.g., log, logit, etc.). Expected crime distributions included binary ($n = 7$), multi-nomial ($n = 3$), count ($n = 10$), and rate ($n = 17$) outcomes.

Intervention time-series assessments used GLMs to analyze the change in monthly rates (Vingilis et al. 2005; Miller et al. 2012; Duailibi et al. 2007; Chikritzhs & Stockwell 2006; Chikritzhs & Stockwell 2007) and counts (Vingilis et al. 2006; E. Vingilis et al. 2008; Mazerolle et al. 2012; Kypri et al. 2011; Evelyn Vingilis et al. 2008) of crime after on-premises outlet lock-out policy changes (Mazerolle et al. 2012; Miller et al. 2012) or alcohol trading hour extensions (Duailibi et al. 2007; Chikritzhs & Stockwell 2007; Chikritzhs & Stockwell 2006; Kypri et al. 2011; E. Vingilis et al. 2008; Vingilis et al. 2006; Evelyn Vingilis et al. 2008; Vingilis et al. 2005). In almost all cases, change in crime was assessed using a dichotomous intervention variable before and after the policy intervention period. Additional covariates were included in half of the studies to control for the impact of socio-demographics, other crimes, dry laws, police force changes (Chikritzhs & Stockwell 2006; Miller et al. 2012; Duailibi et al. 2007) and interactions among age, location and time of drinking (Chikritzhs & Stockwell 2007) on crime. Seventy percent of the intervention studies used quasi control data to test that any change in criminal incidence was the effect of the alcohol policy intervention. Control data were integrated directly into the model by combining the alcohol policy intervention variable with a dichotomous area variable (study area versus control)(e.g., (Kypri et al. 2011)).

More commonly, GLMs were applied to cross-sectional datasets estimating the effects of alcohol access on crime ($n = 23$). Eleven studies aggregated crime and alcohol measures to regional/spatial units to estimate the effects of increased excise tax (Markowitz & Grossman 2000) or alcohol outlet densities on crime rates (Scribner et al. 2010; Scribner et al. 1999; Gerson & Preston 1979; Breen et al. 2011; Speer et al. 1998; Schofield & Denson 2013) and counts (Jennings et al. 2013; Liang & Chikritzhs 2011; Day et al. 2012; Pridemore & Grubestic 2012b), while controlling for area (spatial unit, fixed effect) and demographic characteristics. The remaining 12 cross-sectional studies estimated the probability of crime using individuals' alcohol consumption data (Felson &

Staff 2010; Macdonald et al. 2005; Borges et al. 1998), alcohol access in the respondent's regional area (Wilkinson & Livingston 2012; Wechsler et al. 2002), or nested data investigating both consumption at the individual level and regional alcohol exposure (McKinney et al. 2009; Waller et al. 2012; Iritani et al. 2013; Waller & Iritani 2012; Markowitz 2000; Markowitz 2005; Resko et al. 2010).

Across panel analysis, fixed-effect GLMs ($n = 4$) were specified to estimate the impact of regional alcohol outlets (Parker et al. 2011; Jackson & Owens 2011; Michael Livingston 2011) and change in alcohol tax (Herttua et al. 2008) on monthly count (Jackson & Owens 2011), and annual (Parker et al. 2011; Michael Livingston 2011; Herttua et al. 2008) crime rates. The intervention in alcohol tax policy was monitored using categorical change variable, analogous with the intervention time-series regressions (Herttua et al. 2008). By specifying unit and time fixed effects GLM models maximize explaining the variance within units and years, limiting the possibility that differences between regions and time-periods will bias results (i.e., omitted variable bias).

3.4.3 Hierarchical, non-linear models and extensions

An extension of GLMs are hierarchical models (generalized linear mixed models (GLMM), generalized additive models (GAM)), which were used to account for correlated errors, spatial patterns, and temporal trends ($n = 40$, 44%) across time-series ($n = 1$), cross-sectional ($n = 27$), panel ($n = 8$), and intervention panel ($n = 4$) datasets. Splines, data hierarchies, lagged variables, correlation terms, and random effects (slope and intercepts) addressed non-linear relationships, nested data structures, data dependency between units/time, and unexplained variance, respectively. Bayesian methods were also applied for inference in recent studies (Erickson et al. 2013; Traci L Toomey et al. 2012; T. L. Toomey et al. 2012; Wheeler & Waller 2008; Mair et al. 2013; Cunradi et al. 2011; Yu et al. 2010; McMillan et al. 2007). In contrast to frequentist techniques, Bayesian inference is conditional on both observed data (via the likelihood) and specified prior information for each model parameter to provide a joint posterior distribution for the model parameters. While the full posterior is generally not available in closed form, sampling methods (such as Markov Chain Monte Carlo) can be used to obtain samples from the marginal distributions, which are of primary interest.

The intervention time-series study (Sánchez et al. 2011) applied a negative binomial conditional autoregressive model (adjusted for age, sex, weekends, holidays, event days, government leadership) to estimate the influence of three different alcohol sales restrictions on the daily count of crime over four years. The autoregressive structure corrected for correlation between homicides in time (lagged counts of homicides from 7, 14, and 21 days). Intra annual trends (associated with alcohol policy changes) were modelled using marginal splines, and annual trends and seasonal changes in crime were captured using fractional polynomials and sine-cosine pairs (also known as Fourier terms), representing a thorough consideration of temporal oscillations in criminal activity.

Cross-sectional studies varied in model complexity to estimate the influence of alcohol expenditure (Grubestic et al. 2013), consumption frequency (Gruenewald et al. 2002), or alcohol outlet density ($n = 26$) on the count ($n = 4$) and or rate ($n = 23$) of crime. Four studies published prior to 2004 used hierarchical regression to simultaneously estimate the influence of alcohol outlet density, socio-economic factors (Gorman, Labouvie, et al. 1998; Reid et al. 2003) and their interactions (Gorman, Speer, et al. 1998) on the rate of violent crime across municipalities, accounting for both individual level (frequency of drinking and driving with an intoxicated person) and city wide (alcohol outlet density) alcohol consumption influences on youth drinking and driving (Treno et al. 2003).

A larger portion (76%) of the cross-sectional studies conducted spatial regression to estimate crime rates within block groups ($n = 5$), neighbourhoods ($n = 3$), census tracts ($n = 6$), postal/zip codes ($n = 5$), government areas ($n = 1$), or user defined areas ($n = 1$) areas using spatial lag (SAR) (Grubestic et al. 2013; Livingston 2008; Lipton & Gruenewald 2002; Gorman et al. 2001; Zhu et al. 2004; Gruenewald et al. 2006; Gruenewald et al. 2002; Stevenson et al. 1999; Franklin et al. 2010; A. L. Nielsen et al. 2005; Gorman et al. 2005; Gruenewald et al. 1996; Pridemore & Grubestic 2012a; Costanza et al. 2012), conditional autoregressive (CAR) (Erickson et al. 2013; T. L. Toomey et al. 2012), or spatial error (SEM) (Traci L Toomey et al. 2012; Freisthler et al. 2004; Franklin et al. 2010; Livingston 2010; Zhu et al. 2004). SAR, CAR and SEM models address spatial dependence within the outcome or exploratory variables (correlation of data between analysis units) to avoid spatially clustered residuals and

biased coefficients (Dormann et al. 2007). Spatial lagged models (SAR) include a parameter of interest on the right hand side of the regression equation, calculated in some studies as the weighted average of alcohol outlets (Gruenewald et al. 2006; Gruenewald & Remer 2006) or socio-demographics in neighbouring regions, to estimate the incidence crime. Whereas, the spatial error models (SEM) restrict autocorrelation to the error term assuming missing variable bias, effecting the covariance structure of the random disturbance term (e.g., in (Gruenewald & Remer 2006) the spatial error is a random effect) (Dormann et al. 2007; Anselin 2009). Frequently, spatial models use a contiguity spatial weights matrix to represents the dependency between values or errors at each location and adjacent locations among analysis units, though distance weighted matrices also exist. CAR models, in contrast to SAR and SEM models, assume the state of a particular area is influenced by its neighbours and not neighbours of neighbours (Markov property) applying a symmetric weights matrix.

Pursuant to the spatial models, two cross-sectional studies explored geographically weighted regression (GWR) (Grubestic et al. 2012) or Bayesian spatially varying coefficient process (SVCP) models (Wheeler & Waller 2008) to estimate how alcohol outlet density influences violent crime across local regional areas. In contrast to the spatial regression models above, spatially varying coefficient models do not assume the relationship between alcohol access and crime is constant across space and instead estimate coefficients for regions across the study area (e.g., census tracts or block groups in these cases). The GWR method fits a linear regression model for each location in the dataset using data collected from a specified radius around the point/region, weighted in varying degrees of importance using a kernel function, such that data further away from the units is less influential than data close by (Fotheringham 2009). The “optimal” radius is calculated using cross-validation. In the Bayesian spatial varying coefficient model, random effects (intercept and effect parameters) are defined in the prior and borrow strength from local data exhibiting spatial autocorrelation (defined using contiguity matrix or distance weighted function). The spatially varying coefficient process then uses a prior joint specification of the coefficients that models the spatial correlation of the coefficients as a continuous process (i.e., multivariate conditional autoregressive model)

(Elhorst et al. 2010), and parameter inferences are possible by sampling the posterior distributions using MCMC sampling.

Panel studies used a variety of fixed and random effects modelling, fit with maximum likelihood ($n = 7$) or Bayesian ($n = 2$) estimation, to model how alcohol price (Matthews et al. 2006; Sivarajasingam et al. 2006), excise tax (Son & Topyan 2011), and outlets densities (Mair et al. 2013; Cunradi et al. 2011; Gruenewald & Remer 2006; M. Livingston 2011; White et al. 2015) influenced the incidence of crime over space and time. To ensure cross-sectional and temporal differences did not bias results, researchers applied either space-time fixed (Son & Topyan 2011; Treno et al. 2007; M. Livingston 2011) or random (Sivarajasingam et al. 2006; Matthews et al. 2006; Gruenewald & Remer 2006; Cunradi et al. 2011) effects for units and time periods. In the fixed effects models, researchers considered the lagged effects of alcohol access or socio-demographics over time (M. Livingston 2011; Son & Topyan 2011) or space (Treno et al. 2007) on the incidence of crime, but did not explore space-time interaction.

In a more complex panel model, Poisson Bayesian space-time misalignment analysis was conducted to estimate how alcohol outlet density in focal region and neighbouring zip codes (lag) effected the count of assault injuries over 14 years (Mair et al. 2013). The Bayesian spatial misalignment model addressed how the geographic delineation of zip codes varied over the study period. The authors specified a CAR random effect for each year's spatial adjacencies to control the influence on autocorrelation between units. A random county and country level effect were also used to control for the nested structure of the zip codes, and year specific intercepts were implemented to assess statewide changes in assault risk not explained by the neighborhood demographics, alcohol outlet densities, overall hospitalization rates, population density, retail clutter, presence of highways, and ZIP code instability (misalignment) covariates. Successive models were run to explore additional lags and bar interactions effects on crime.

In the less common intervention panel studies ($n = 4$), applying mixed modelling techniques, researchers contended with space-time effects and monitored if a significant change in the incidence of crime occurred after a change in alcohol outlet closing times (Biderman et al. 2009), allowance of Sunday alcohol sales from packaged retail stores

(McMillan et al. 2007), alcohol tax increase (Cook & Durrance 2013), or decrease in alcohol outlets (Yu et al. 2010). In two cases, fixed effects were used to model the influence space and time units on crime (Cook & Durrance 2013; Biderman et al. 2009) though both studies explored temporally lagged influences on crime including: alcohol consumption per capita (Cook & Durrance 2013) and change in municipal dry laws (Biderman et al. 2009). Finally, dummy variables were used to signify if a significant shift in the rate of crime occurred after an alcohol tax change (Cook & Durrance 2013) or restricted alcohol outlet closing times (Biderman et al. 2009).

The random effects panel studies ($n = 2$), applying Bayesian estimation, modelled the change in quarterly count of alcohol-related crashes post lifting alcohol sales ban across 33 counties (McMillan et al. 2007) and the change in probability of assaultive violence after and alcohol licenses surrenders across 480 census tracts (Yu et al. 2010). The probability of a crash was estimated using previous quarterly state-rate of crashes, the yearly change in crash rate, socio-demographic controls and a random intercept indicating the change in Sunday sales of alcohol (zero before, mean sales after sales ban). Weakly informative priors were specified for each parameter in the model leaving the posterior inferences largely influenced by the dataset. A CAR model was used to monitor changes in assaultive violence after outlet licence surrender assuming a Poisson distribution for crime data. Alcohol exposure was measured as a dichotomous indicator of census tracts surrendering alcohol licenses, the percent of surrender, alcohol outlet density, and a dual change point interaction term specifying the year and tract. Control covariates included yearly: race, young male population, poverty, and damage per square mile, and a spatial error. The spatial error model accounted for residual similarities across neighbourhoods specifying the prior mean of the error in the focal tract should be equal to the average error in the adjacent census tracts (gamma hyperprior distribution having mean 1 and variance 10 used). All other covariates priors were specified as having a normal distribution centered at 0 with precision 0.00001 (i.e., non-informative). Marginal posterior distributions for all parameters were obtained via Markov chain Monte Carlo (MCMC) sampling.

3.4.4 Regression Trees, Cluster Detection, and Mapping

Pursuant to traditional effects modelling, Multiple Additive Regression Tree method ($n = 1$) was applied to account for the effects of a percent change in alcohol-license outlets on violent crime rates after multiple alcohol-license surrenders in Los Angeles California (Yu et al. 2009). Regression trees are a computationally intensive, non-parametric method, of recursively splitting data based on thresholds of the singular variables to maximize the homogeneity within the resulting response groups (e.g., crime rates), using (in some cases) the analysis of variance (Prasad et al. 2006). The resulting tree shows a hierarchy of selected explanatory variables, and interactions among, though no formal coefficient estimation or significance testing are available (De'ath & Fabricius 2000). To avoid over fitting and provide a more rigorous evaluation of explanatory variables influence on the model fit, bagging and boosting regression trees ensemble methods were developed. These methods use multiple trees, derived from sub-samples or residual data to predict the response (crime) to stabilize model results (Friedman & Meulman 2003). Yu et al., (Yu et al. 2009) study included a continuous measure of on and off license alcohol outlets densities per square mile from 1990-1999, the proportion of licenses surrender after civil unrest, and accounted for spatial structure using a CAR term to explain the variance in violent rates across census tract units of Los Angeles California.

Beyond estimation approaches, alcohol and crime studies have emphasized mapping and graphing as valuable techniques for identifying spatio-temporal patterns between crime and alcohol consumption for policing ($n = 5$). Space-time mapping was conducted to understand how liquor violations, assaults, batteries, vandalism, and noise complaints emerged through time and space in proximity to the university bar district of Madison Wisconsin (Brower & Carroll 2002). Graphing identified the temporal distribution and proportion of assault per alcohol establishment license type in the Newcastle & Wollongong Australia (Briscoe & Donnelly 2003). Spatial cluster methods illuminated where alcohol outlet densities and crime rates frequencies significantly diverted from an expected random pattern (Grubestic & Pridemore 2011) and cellular automata models were used as the first prospective (forecast) analysis to assess how relative risk ratios of crime (crime as a proportion of alcohol density) were expected to

disperse with changes in population at risk across a detailed (50m resolution) downtown Vancouver British Columbia study (Spicer et al. 2012).

Specifically, the spatial cluster method identified agglomerations of alcohol outlet densities using an empirical Bayesian rate standardizing scores per roadway mile, and then applied a Moran's I local analysis to identified block groups (lag 1 contiguity) where the rate of alcohol outlets exceeded the mean overall rates, and significantly departed from what would be expected under a random assignment of alcohol outlets across the study region (Anselin 1995). Alcohol outlet agglomerations were compared to regional violence counts using a foci cluster test specified as the sum of the differences between observed and expected assault counts at each location weighted by the exposure to alcohol outlet agglomeration. In this sense, the statistic explained a distance decay effect identifying the spatial extent at which the observed number of assaults exceed the expected (Grubestic & Pridemore 2011).

Cellular automata methods, similar to agent based modelling, forecasted crime dispersion based on spatial distribution of alcohol outlet seats using a 50m grid across the Vancouver area. Each grid cell was specified with a number of finite states of possible violent crime risk, and a contiguity neighbourhood around each cell was defined. The initial state of each cell was trained by observed alcohol outlet seats and violent crime risk. A new state for each cell was created according to a fixed rule (blocks with high relative risk were specified to increase violent crime frequency) conditional on the current state and of the cells in the adjacent neighbourhood. The simulation was run 2300 times and in each case high risk violent crime blocks multiplied when liquor licenses clustered, creating the first prospective analysis of alcohol exposure and criminal behaviour.

3.5 Discussion

3.5.1 Methods

A large variety of modelling and exploratory techniques were applied to study the effects of alcohol exposure on criminal behaviour (Table 3.4). Datasets varied in exposure indices and spatial and temporal detail from large state/city/district overviews of crime

rate changes after alcohol policy changes (Mazerolle et al. 2012; Miller et al. 2012; Kypri et al. 2011; Cook & Durrance 2013) to detailed block level analysis of alcohol outlet density and crime clusters (Grubestic & Pridemore 2011; Spicer et al. 2012) with each providing unique information for alcohol policy planning. Policy makers are interested in how exposure to alcohol affects overall population rates of crime, while also wanting to address neighbour needs for policing around troublesome alcohol establishments, local zoning policy, or approval of new alcohol establishments (Babor et al. 2010). Therefore, estimation and prediction techniques were mindfully selected to provide guidelines for alcohol-crime prevention. We address the strengths and weaknesses of common quantitative approaches, and data collection methods to guide future alcohol-crime research.

Table 3.4 Applied quantitative methods

Method	Type	Application	Suitable Dataset Structures	Considerations	Applied
ARIMA	Model	Forecasting model used to predict crime-trends (rates or counts) through time. Most often used to understand if the rate or count of crime changed after an alcohol policy intervention.	Times-series	Times-series must be stationary, which can remove information about the temporal patterns of criminal behaviour.	(Norström 2000; Bloomfield et al. 2009; Gustafsson & Ramstedt 2011; Ingeborg Rossow & Norström 2012; Norström & Skog 2003)
GLM	Model	Regression model used to understand how alcohol consumption or alcohol exposure in an area influences crime (rates, counts, odds) across space and or time using fixed effects. Policy interventions were monitored using a dichotomous intervention variable.	Times-series Cross-sectional Panel	Model residuals must be independent between analysis units (time and or space).	(Mazerolle et al. 2012; Miller et al. 2012; Duailibi et al. 2007; Chikritzhs & Stockwell 2006; Chikritzhs & Stockwell 2007; Kypri et al. 2011; E. Vingilis et al. 2008; Vingilis et al. 2006; Vingilis et al. 2005; Evelyn Vingilis et al. 2008; Markowitz & Grossman 2000; Scribner et al. 1999; Gerson & Preston 1979; Breen et al. 2011; Speer et al. 1998; Jennings et al. 2013; Liang & Chikritzhs 2011; Day et al. 2012; Pridemore & Grubestic 2012b; Schofield & Denson 2013; Parker et al. 2011; Jackson & Owens 2011; Michael Livingston 2011; Herttua et al. 2008; Scribner et al. 2010; Resko et al. 2010; Markowitz 2005; Markowitz 2000; Waller & Iritani 2012; Felson & Staff 2010; Iritani et al. 2013; Macdonald et al. 2005; Wechsler et al. 2002; Borges et al. 1998; McKinney et al. 2009; Wilkinson & Livingston 2012; Waller et al. 2012)
Hierarchical, non-linear models and extensions (GLMM)	Model	Extended regression models used to estimate crime (rates, counts, odds) across space and time as a function of alcohol consumption, access, or other	Times-series, Cross-sectional Panel	Model residuals must be independent between analysis units (time and or space).	(Grubestic et al. 2013; Livingston 2008; Erickson et al. 2013; Traci L Toomey et al. 2012; T. L. Toomey et al. 2012; Gorman, Labouvie, et al. 1998; Gorman, Speer, et al. 1998; Lipton & Gruenewald 2002; Freisthler et al. 2004; Gorman et al. 2001; Zhu et al. 2004; Gruenewald et al. 2006;

		<p>explanatory variables. Effects were random, or mixed, and sometimes hierarchical in structure. Temporally or spatially lagged variables were explored. SAR, CAR, SEM extensions provided useful techniques for modelling spatial autocorrelation across small contiguous unit studies (e.g., census, postal, neighbourhood, block). Policy interventions were monitored using a dichotomous intervention variable.</p>			<p>Treno et al. 2003; Gruenewald et al. 2002; Reid et al. 2003; Stevenson et al. 1999; Franklin et al. 2010; A. L. Nielsen et al. 2005; Gorman et al. 2005; Livingston 2010; Gruenewald et al. 1996; Pridemore & Grubestic 2012a; Costanza et al. 2012; Treno et al. 2007; Matthews et al. 2006; Son & Topyan 2011; Mair et al. 2013; Cunradi et al. 2011; Gruenewald & Remer 2006; Sivarajasingam et al. 2006; M. Livingston 2011; White et al. 2015; Yu et al. 2010; McMillan et al. 2007; Cook & Durrance 2013; Biderman et al. 2009; Sánchez et al. 2011)</p>
GWR and Bayesian SVCP	Model	<p>Regression models used to specify regional coefficients to address spatial heterogeneity (data relationships that vary across space). Bayesian SVCP method offered a robust statistical estimation, over GWR.</p>	Cross-sectional Panel (Data must be spatially aggregated to points, grid, or contiguous polygons)	GWR is vulnerable to multiple significance testing. Estimated coefficients should not exhibit positive spatial autocorrelation.	(Grubestic et al. 2012; Wheeler & Waller 2008)
Regression Tree	Non-parametric model	<p>Non-parametric recursive partitioning method used for modelling crime rates or counts as a function of multiple explanatory variables including categorical variables,</p>	Time-series Cross-sectional Panel	No formal coefficient estimation or significance testing available.	(Yu et al. 2009)

		spatial lagged variables, or CAR terms to model spatial or temporal trends. Policy interventions monitored using dichotomous intervention variable.			
Cluster Detection (e.g., Local Moran's I)	Statistical test	Statistical test used to identify (map) areas of high crime or alcohol exposure concentrations.	Cross-sectional (Data must be aggregated to contiguous spatial units)	User defined spatial weights matrices can influence cluster results. Irregular spatial units can also bias results.	(Grubestic & Pridemore 2011)
Cellular automata	Systems model	Discrete model used to predict future crime dispersion based on changes in alcohol exposure using a set of user defined "rules". The model began with a grid, a fixed state for each cell, and a rule for transformation of the "state" over time.	Cross-sectional Panel (Data must be superimposed onto a grid)	No formal statistical estimation. System rules (algorithms) are user defined.	(Spicer et al. 2012)
Mapping and graphing	Visual and quantitative method	Used to assess if the distribution of crime coincides with alcohol exposure over space and time.	Cross-sectional Panel	No formal statistical estimation. Limited ability to access multiple effects on the distribution of crime.	(Briscoe & Donnelly 2003; Douglas 1998; Brower & Carroll 2002)

ARIMA modelling was used for 33% of the intervention time-series studies, with the most recent published in 2012 (Ingeborg Rossow & Norström 2012). While it is possible to use ARIMA models for change point analysis, some limitations exist; namely, the removal of temporal trends and seasonal oscillations in crime during the differencing technique to ensure stationarity among the crime series (Cheng et al. 2014). By removing information about the timing of crime one is limiting information for crime prevention strategies and information for local alcohol policy/zoning. Further, the structure of the ARIMA model challenges researchers ability to contend with missing data or explore stochastic exploratory effects on the alcohol-crime relationship (Norström & Ramstedt 2005). Therefore, it is not surprising that 54% of the intervention time-series studies used regression to quantitatively summarize any changes in the incidence of crime post regional alcohol policy changes.

Regression modelling was the most commonly used method of crime estimation (86%) spanning the widest variety of datasets (cross-sectional, time-series, panel and intervention) and distributional characteristics (Section 3.3.3 & 3.4). GLMs (41% of studies) had the advantage of testing constant and seasonal trends on crime, in addition to alcohol exposure, over methods such as hypothesis testing (e.g., chi-square (El-Maaytah et al. 2008; Graham et al. 1998)). However, there were drawbacks when considering the statistical assumption of: independence between crime measures, correct specification of link and variance functions, little to no multi-collinearity among the explanatory variables, and independent uncorrelated residuals.

A limitation of the intervention time-series studies applying GLMs, without fixed time effects ($n = 5$), included the assumption that monthly crime data were independent between time periods and any changes in alcohol policy would have an immediate effect on crime. Ignoring implication of time can cause positive serial autocorrelation in errors, and miss any time-lagged effects of the alcohol exposure on crime (Sridharan et al. 2003). Notably, when serial autocorrelation exists between the temporal units the significance of the intervention variable can be overestimated. A small number of the ($n = 5$) intervention studies did test for data dependence between months (Miller et al. 2012; Duailibi et al. 2007; Chikritzhs & Stockwell 2006; Vingilis et al. 2006; Evelyn Vingilis et al. 2008) and one corrected for secular and seasonal effects on alcohol consumption and

crime (Kypri et al. 2011), though half of the results may have been vulnerable to untested temporal bias. Intervention time-series analysis may be better addressed by mixed modelling approaches incorporating time lagged explanatory variables or structured time series methods that explicitly address trends and seasonality inherent in crime data.

Spatial autocorrelation was an underlying concern for contiguous ($n = 10$) multi-regional cross-section studies applying fixed linear regression, most often, to study the regional effects of alcohol density on violent crime. Data dependence (positive correlation) between units can lead to correlated residuals, ultimately reducing the standard error and biasing coefficients (Anselin 2009; Cliff & Ord 1981). More recent publications (published since 2011) tested for residual spatial autocorrelation (Breen et al. 2011; Jennings et al. 2013; Liang & Chikritzhs 2011; Day et al. 2012; Pridemore & Grubestic 2012b) though half did not address the independence assumption. When positive autocorrelation was found, one study remedied significant spatial autocorrelation by removing spatial units instead of applying a more appropriate spatial lag or error model (See Section 3.4.2).

A further concern of the cross-section studies was the application of GLM technique to nested data ($n = 7$). Nesting often occurred when researchers were modelling the influence of both individuals' consumption habitats and regional alcohol exposure on the individual level incidences of crime. Without specification of the hierarchies (e.g., generalized linear mixed model) it is possible that correlated errors exist among groups (e.g., dependence between responses pulled from the same regional area/level of alcohol access) which can under estimate standard errors, and in some cases, incorrectly specify the magnitude of the explanatory effects (see (Garson 2013)).

Panel studies applying fixed effects on the unit and time covariates ($n = 4$) sacrificed statistical power to avoid omitted variable bias as the degrees of freedom diminish for every space and time unit. The models become vulnerable to over fitting as the space and time effects are not generalizable to other regions and time periods. Understanding intra space-time patterns is key for alcohol policy planning. In order to address space-time effects one study applied a jackknifing approach to monitor the impact on the estimated coefficient when one space-time period is left out of the analysis (Parker et al. 2011). Researchers would further benefit from the specification of random

space time effects, especially with shorter time-periods and a greater amount of spatial units, in order to conserve statistical power (Clark & Linzer 2012). Panel models should also consider the implications of alcohol access in previous units and regions as well as within unit variance.

Hierarchical models (e.g., GLMM, GAM, and Bayesian SVCP) were better suited for estimation when addressing the complex framework of alcohol-crime studies incorporating data from multiple regions and time-periods. Specifically random effects modelling permitted the influence of explanatory variables to fluctuate over space and time (random slope or intercept model) and can be keenly useful when addressing spatial variation in the expected outcome (Clark & Linzer 2012). For example, you can condition the estimated value of crime toward the mean for regions with fewer persons instead of predicting extremely low numbers (Robertson et al. 2010; Clark & Linzer 2012), particularly useful for small scale regional modelling (e.g., census, neighbourhood, blocks). Further, hierarchical models can estimate the effects of explanatory variables on crime measured at multiple scales allowing researchers to consider direct factors (e.g., alcohol blood level) and environmental effects (e.g., regional alcohol outlet density, or demographics) on the incidence of crime. Mixed modelling also offer approaches for modelling autoregressive processes (lagged or spatial error models) when the space and time detail in data increase such that researchers have to consider the effects of alcohol access in previous time periods or neighbouring units on the incidence of crime. Alcohol consumption in one neighbourhood can lead to crime in an adjacent or further region and changes in alcohol policy may have a delayed influence on crime incidence as the population recognizes modifications, increasing the importance of considering lagged variables.

Bayesian estimation also provided flexible inference methods for modelling hierarchies (Traci L Toomey et al. 2012; T. L. Toomey et al. 2012) space (Wheeler & Waller 2008; Mair et al. 2013), and space-time (Cunradi et al. 2011; McMillan et al. 2007; Yu et al. 2010) dynamics. Improving upon frequentist techniques, Bayesian Spatially Varying Coefficient Process offer inference possibilities for modelling non-stationary datasets (controlling for correlation among regionally estimated regression coefficients), in contrast to GWR models which use an iterative algorithm lacking formal

statistical properties of inference (Elhorst et al. 2010). Because of these advantageous we are seeing a recent trend in the publication of Bayesian inference across the alcohol-crime literature (seven published since 2007) most likely influenced by the increasing hierarchical and space-time detail of data and free software (e.g., WinBugs) for model fitting and computationally intensive sampling of the posterior distributions for estimation.

In addition to mixed modelling techniques, we also see utility in the less common applied exploratory methods, specifically cluster detection and density mapping, which can illuminate specific risk locations of alcohol-related crime (Braga 2005). Cellular automata also poses an alternative prospective modelling approach where known information about alcohol exposure and crime can train a computation model to predict where crime will lead in future scenarios of exposure (Spicer et al. 2012). However, these methods lack tradition coefficient estimation, statistical significance testing, and limit the ability to study simultaneous effects on crime. Parameters are often specified by the user (e.g., cellular automata “rules” and weight matrices in cluster detection) introducing user bias. What they do provide is local specification of high risk areas for policing and regional planning, and unique methods for predictive simulations when alcohol exposure increases (e.g., additional retail stores, on-premises drinking establishments, or extended hours of sales).

3.5.2 Future research

Pursuant to modelling considerations we found the practice of standardizing crime counts by residential population data predominant across rate calculations. It is likely when using smaller geographic units (blocks or neighbourhood) for analysis the residential population is unrepresentative of population at-risk (Gruenewald 2007) displacing the true spatial pattern of crime (Malleon & Andresen 2014) thereby altering model results for small areas studies. For example, people living in an area are not necessarily the population consuming alcohol and committing crime. Often establishments that sell alcohol draw people from neighbouring regions to their premises altering the population at risk in time and space (Gorman et al. 2013). Depending on the study, using residential population counts can skew the relative risk scenario of crime and

alter relationships estimated in models applying residential population rates, especially across smaller areas such as blocks, census tract, or neighbourhoods where persons could readily venture between. Opportunities exist to use ambient population data (data representing the spatial and temporal fluctuations of populations). Products such as Landscan Data (1km resolution, <http://web.ornl.gov/sci/landscan/>) or social media crowd sourced data (Malleson & Andresen 2014) can be used to gain dynamic population estimates for improved rate calculations and provide population information for retrospective and prospective modelling. Landscan data redistributes residential population counts, using complex land use models, to identify where persons are mostly likely to spend their time in a 24hr period. Whereas, social media demographic estimates pin media users to the geographic location in time showing demographic variances across space and time, and are likely to represent the younger drinking population vulnerable to nuisance and assault crimes (Babor et al. 2010; World Health Organization 2011; Connor et al. 2011).

Emphasis on the accurate measurement of alcohol exposure is also prudent with the majority of analysis (89%) inferring causation using exposure measures (alcohol outlet density, hours of sales, alcohol sales volumes, and trading hours) instead of direct consumption information (blood alcohol level, drinking frequency). Generally, we found studies exploring direct alcohol consumption indicators (blood alcohol level and consumption patterns) identified positive significant results between alcohol consumption and crime (Chikritzhs & Stockwell 2007; Felson & Staff 2010; Macdonald et al. 2005; Borges et al. 1998; Scribner et al. 2010; Resko et al. 2010; Waller & Iritani 2012; Waller et al. 2012; Cook & Durrance 2013). Whereas studies using alcohol exposure measures such as alcohol sales lock-outs (Mazerolle et al. 2012; Miller et al. 2012), change in the hours of sales (Duailibi et al. 2007; Chikritzhs & Stockwell 2006; E. Vingilis et al. 2008; Vingilis et al. 2006; Norström & Skog 2003), change in establishment hours (Graham et al. 1998), modification of alcohol tax (Son & Topyan 2011; Herttua et al. 2008; Bloomfield et al. 2009; Gustafsson & Ramstedt 2011) or alcohol outlets (measured at the municipal level) (Gorman, Labouvie, et al. 1998; Gorman, Speer, et al. 1998) found no significant relationships. Insignificant findings, were exclusive to time-series (Bloomfield et al. 2009; Gustafsson & Ramstedt 2011; Miller et al. 2012; Chikritzhs & Stockwell

2006; E. Vingilis et al. 2008; Vingilis et al. 2006; Graham et al. 1998), cross-sectional (Gorman, Labouvie, et al. 1998; Gorman, Speer, et al. 1998), and panel (Herttua et al. 2008; Son & Topyan 2011) assessments aggregating data to large spatial units such states ($n = 1$), countries ($n = 5$), cities ($n = 3$), or municipalities ($n = 2$), which may indicate that both the type of index and level of spatial aggregation can mask effects. Overall the choice of scale is limited to available data and we can not make conclusions across scales, though improvements can be made to alcohol exposure measures. Simply the difference in measurement of alcohol outlet density per region is one example. Regions of equal outlets and populations can have vastly different access if spread across difference sized areas. Similarly standardizing by area does not represent the paths people readily use for travel. While most studies standardize outlet density by population per region (Gorman et al. 2001) or per area (Cunradi et al. 2012), roadway standardization is regarded as a preferred method of representing “access” (Grubestic et al. 2013).

Further, many studies combine alcohol establishment types to model the association between crime and indicators of consumption (Zhu et al. 2004; Wheeler & Waller 2008; Waller et al. 2012; Resko et al. 2010; Reid et al. 2003; Parker et al. 2011; A. L. Nielsen et al. 2005; Gyimah-brempong 2001; Gorman, Speer, et al. 1998). However, it has been established that specific establishments types contribute disproportionately to increasing the rates of crime (Newton & Hirschfield 2009; Briscoe & Donnelly 2003). To illuminate these connections researchers need disaggregate alcohol establishments, especially across small unit studies where correlation among densities is less likely. Additionally, researchers could explore attributing density measures with seating capacities as not to treat each establishment as having an equal weight on consumption patterns (Spicer et al. 2012). Only one study represented on-premises alcohol outlet density using seats (Spicer et al. 2012).

We recognize the limitations surrounding the level of spatial and temporal detail available for crime models using traditional data sources, such as aggregated police data or government records. We see utility in assessing if social media can be used to track alcohol consumption and crime patterns in space and time by searching user’s messages on twitter feeds. The information content provided by social media is being utilized in health research (Scanfeld et al. 2010), and could prove resources for crime and alcohol

studies. Participatory mapping, where respondents connect responses in space and time on a geographic interface, could also become a more common application across the consumption and crime surveys to source information about the probable locations of alcohol consumption and witnessed alcohol-attributable crime. The advantages of participatory data collection for health research are well known (Cargo & Mercer 2008; Burke et al. 2005), but have not extended to crime-alcohol modelling.

Regarding dataset structures, the robustness of cross-sectional studies ($n = 43$) could be improved by increasingly collecting data that link intoxication level and the place of last consumption, to the location of the crime. For example, in studies, such as Chikritzhs & Stockwell (Chikritzhs & Stockwell 2007) and Macdonald et al. (Macdonald et al. 2005), researchers analyzed crime records in conjunction with blood alcohol levels and place of last consumption. These studies are well poised to draw hierarchical connections between individuals and environmental influences on drinking patterns and subsequent criminal behaviour. Other researchers applied a local-level analysis to gain insights on the frequency of crime in and around alcohol establishment's linking offences with the types of alcohol outlets (Mazerolle et al. 2012; Briscoe & Donnelly 2003; Chikritzhs & Stockwell 2002; Gerson & Preston 1979). Studies connecting consumption to specific locations are invaluable crime prevention, but scarce across the literature.

When smaller regions are studied, health researchers have noted the distance effects of alcohol availability within regions on neighbouring regions' crime rates, and these influences have been observed by fitting models with spatially lagged variables where within each spatial unit crime rates are predicted by establishments within neighbouring areas (Gruenewald et al. 2006; Gruenewald & Remer 2006). Rarely in these studies are the effects explored outside of the adjacent areas (e.g., (Gruenewald et al. 1996; Mair et al. 2013)); however, as the spatial units become smaller (i.e., blocks) the movement of intoxicated individuals across more than one spatial unit is likely and researchers should address the distance at which the effect is negligible by using multiple spatial lags within small area studies.

To date, explicitly addressing the concept of proximity between alcohol establishments and crime is limited (Wilkinson & Livingston 2012; Grubestic & Pridemore 2011). With advances in technology for mapping alcohol establishment and

crimes, it is possible to address the diffusion of crime around each establishment in space and time. Using distance decay functions (Leary & O'Leary 2011; Kent et al. 2006; Lynch & Moorcroft 2008), parameters can be quantified to explain the expected frequency of crime as a function of distance by treating alcohol establishment locations (or clusters) as the origins of crime. Space-time bivariate point pattern analysis (Lynch & Moorcroft 2008) can also statistically assess the spatial extent (i.e., radius) crimes cluster around outlets. These results would provide evidence based information for setting restrictions on the proximity of alcohol establishments in an area. Only one known study has explored bi-variate Ripley's k-function to determine the distance at which point level crime data clusters around alcohol establishments (Conrow et al. 2015) and additional analysis is need to understand if these distance thresholds are consistent across study areas for implementing policy.

Mapping has been largely overlooked analysis strategy, likely because of the privacy concerns associated with crime data. Out of the 90 studies summarized, 18 mapped the distributions of alcohol access and/or crime, and to a lesser extent fitted model values or errors (Yu et al. 2009; Britt et al. 2005; Yu et al. 2010). However, maps can illuminate data outliers and applicable spatial scales for model assessment. Criminologists to date have had a vested interest in understanding the frequency of crime through space and time and studies have been conducted to address the stability of crime hot-spots (Ratcliffe & Rengert 2008; Johnson 2004). In the cases where alcohol establishment densities remain static, it is still useful to study how crime hot spots emerge through hours of the day around these establishments. To observe how clusters of crime form over time three dimensional kernel density mapping (Nakaya & Yano 2010), or scan statistics (Kulldorff 2001) are possible approaches, providing a novel and interesting perspective for alcohol policy literature.

Identifying thresholds at which alcohol access substantively increases crime rates is also an interesting avenue of future studies. Both Livingston (Livingston 2008) and McKinney et al. (McKinney et al. 2009) observed that violent crimes exponentially increased when the count of alcohol establishments met or exceeded 25 units per postal or zip code. These findings signify a change in the environment, merging from community areas to entertainment districts. To understand if these thresholds are cross-

regionally or cross-culturally stable, it is of interest for criminologist and health researchers to employ modelling techniques that can accommodate non-linear response relationships, either in the form of transformed specification before modelling (i.e., GLM, GLMM), or non-parametric methods such as regression trees (Prasad et al. 2006).

3.6 Conclusion

Study designs and statistical approaches characterizing the relationship between crime and alcohol are best chosen based on the research question and nature of data. Researchers studying the influence of alcohol exposures on the rate or count of crime over large areas using multiple spatial units (census tracts, neighbourhoods, blocks) will likely turn to spatial regression, hierarchical models, and spatial varying coefficient models to capture spatial effects. While, crime data collected over areas considered to be demographically homogenous will mostly likely apply time-series analysis to understand how alcohol policy affects crime over larger population groups. Novel sources of spatial data are going to create further opportunity to utilize non-traditional methods to study how the size and capacity of drinking establishments impacts consumption and ultimately crime, across space and through time. There are new techniques available for rate calculations across small analysis units, and we anticipate a surge in the spatio-temporal analysis of the alcohol consumption and crime connection. There is a need to inform policing and alcohol policy by identifying how consumption in specific locations influences regional crime. With advances in spatial-temporal data collection we expect a continued uptake of flexible Bayesian inference, greater inclusion of spatio-temporal point pattern analysis, and prospective modelling over small areas.

4 Chapter 4

The positive effects of increased foot patrols on the incidence of liquor infractions and assaults in the Granville Street Entertainment Area of Vancouver British Columbia Canada

Abstract

Entertainment districts have high crime rates. Offences peak on the weekend during the operating hours of on-premises drinking establishments. To determine if proactive policing from May to September reduced the spatial density (kernel) or annual frequency of liquor infractions and assaults in Vancouver British Columbia Granville St. Entertainment Area (GEA) we analyzed the spatio-temporal pattern of crime in proximity to alcohol licenses before and after the intervention. Pre (2006) and post (2010, 2013) the policing intervention, areas with the highest density of crime (top 5%) were less than 60m away from a nightclub, and crime occurred most frequently between 1:00am and 3:00am. The frequency of weekend liquor infractions and assaults significantly decreased during the proactive policing period ($p < .05$). The magnitude of the reduction was greater for liquor infractions (58% (2010), 69% (2013)) than assaults (16% (2010), 32% (2013)). Future patrolling should focus on north-east end of Granville St during early morning hours (1:00am-3:00am), and consider additional patrols, to increase crime reductions. Nightclubs licensing should be limited, to reduce the magnitude of alcohol-related crime. In light of the recent trend to liberalize alcohol access across British Columbia we demonstrated that targeted policing strategies can reduce alcohol-attributable crime, and provided fine temporal and spatial scale information on the patterns of crime to develop evidence-based information for policing strategies.

4.1 Introduction

Entertainment districts are an enjoyed aspect of night life in cities; however, they also contribute to higher crime rates. In areas with greater alcohol access, the frequency of violent crime (Wheeler & Waller 2008; Conrow et al. 2015; Schofield & Denson 2013; T. L. Toomey et al. 2012; Costanza et al. 2012; Jennings et al. 2013; Franklin et al.

2010; Day et al. 2012; Zhang et al. 2015; Han & Gorman 2013; Zhu et al. 2004; Fitterer et al. 2015) and amenity problems (public intoxication, disturbance, disorderly conduct, vandalism, and property crime) increases (Wilkinson & Livingston 2012; Traci L Toomey et al. 2012). Drinking establishment hours and densities alter the spatial and temporal patterns of criminal offences. Assaults and disorderly crimes occur with higher frequency in and around on-premises drinking establishments, such as pubs and nightclubs (Conrow et al. 2015; Ratcliffe 2012; Burgess & Moffatt 2011; Nicholas et al. 2007; Chikritzhs & Stockwell 2002; McFadden et al. 2015), and offences increase during the operating hours of on-premises drinking establishments, peaking at closing time when intoxicated individuals interact (Mazerolle et al. 2012; Humphreys et al. 2013; Kyprri et al. 2011).

A greater number of alcohol establishments (Gruenewald et al. 1993; Stockwell et al. 2009; Connor et al. 2011; Campbell et al. 2009), longer alcohol sales hours (Chikritzhs & Stockwell 2002; Norström & Skog 2005), and lower liquor prices (Baldwin et al. 2014) are known to increase alcohol consumption, and subsequent harm (Popova et al. 2009; Campbell et al. 2009; Fitterer et al. 2015; Stockwell & Chikritzhs 2009; Wagenaar et al. 2010). Pairing the effects of intoxication (impaired judgement) with alcohol establishments that attract deviant individuals (Bromley & Nelson 2002), vulnerable people (Graham et al. 2006; Quigley et al. 2003), and heavy drinkers (Hughes et al. 2008) into crowded, loud, and poorly ventilated venues the likelihood of crime increases (Lipton & Gruenewald 2002; Livingston et al. 2007; Stockwell et al. 1993; Green & Plant 2007; Hughes et al. 2011). In particular, heavy drinking clientele are prone to aggression (Wells & Graham 2003), partially explaining why disorder, violence, and alcohol establishments cluster in entertainment regions.

Alcohol-attributed crime is avoidable, but poses substantial implication for community safety. In Canada, approximately 30% of crimes are committed while intoxicated (Pernanen et al. 2002). Alcohol policy restrictions are popular policy methods to reduce consumption and harm (limits on price, hours, and establishments) (Campbell et al. 2009; Popova et al. 2009). However, the effects are mixed with most evidence-based analysis has been conducted over broad scales (postal code, census tract) rather than within entertainment regions (Fitterer et al. 2015). Since British Columbia

liberalized alcohol policies to increase hours of sales, and allow more sales establishments (Government of British Columbia 2015a) the public will rely on police patrolling to control the rate of alcohol-related crime. Targeted patrolling of crime hot spots (crime clusters in small areas) is a successful method for crime reduction (Braga et al. 2014).

Responding to escalating violence in Granville Street Entertainment Area (GEA) of Vancouver British Columbia the Vancouver Police began street closures and increased police patrolling in August 2007 on Friday and Saturday nights. During these closures 16 officers are employed to greet people and monitor the area. Subsequent closures have occurred each year from May to September (Matthews 2009). The goal of our study was to use density mapping techniques and interrupted time-series regression to determine if the spatial and temporal patterns and overall frequency of liquor infractions and assaults changed since the 2007 street closures. Our study addresses the need for small scale analysis (within entertainment regions) of spatial dynamics of alcohol-related crime (Fitterer et al. 2015; Fitterer & Nelson 2015) and contributes to the limited number of proactive policing assessments completed within entertainment districts (e.g., de Andrade et al. 2016; Mazerolle et al. 2012). We discuss the success of increased patrolling within the GEA, critique patrol strategies, and highlight areas and times that have the highest frequency of crime, and their proximity to primary licenses to direct patrolling efforts and alcohol licensing policy.

4.2 Methods

4.2.1 Study area

Granville Entertainment Area is an entertainment district in western Canada's largest metropolitan city, Vancouver, British Columbia, Canada. The GEA is known for its high concentration of on-premises alcohol establishments, drawing people from nearby districts to its central nightlife (Figure 4.1). The total capacity of liquor seats reached maximum capacity at 6,700 seats. The area is considered saturated and no new licensed seats are permitted. The latest a trading licensed venue can serve alcohol is 3:00am, while the pubs close at 12:00am, representing two times when intoxicated

patrons influx the area. In 2006 liquor infractions and assaults occurring between midnight and 5:00am reached 1,491 incidences, by 2013 the frequency had reduced to 533 offences. The majority ~70% of liquor infractions and assaults occur during the weekend early morning hours (72% in 2006 and 66% in 2013).



Figure 4.1 Displayed are the locations of liquor primary licenses of on-premises drinking establishments within the Granville Street Entertainment Area of Vancouver British Columbia Canada. Liquor establishment data were downloaded from the British Columbia Liquor Distribution Branch. Hotels are prominent in the south-west end and nightclubs in the north-east end.

4.2.2 Data

To analyze the spatial pattern of alcohol-attributable crime and changes in the frequency of offences, post the entertainment distinct street closures, the Vancouver police provided research restricted liquor infractions (consumption in a public place and public intoxication) and assaults (common, aggravated, sexual, against a police officer,

and with a weapon) data. These data were aggregated and anonymized prior to release. Quasi control (comparison) data including traffic violations, mischief, drug, robbery, burglary, and disturbance offences, not specifically targeted by increased policing, were also provided. Offences occurred within the GEA over the years 2006, 2010 and 2013. Data were stratified by the police between 00:00h and 05:00h to capture alcohol-related offences, a timeframe suggested by multiple alcohol-crime researchers (Mazerolle et al. 2012; Chikritzhs & Stockwell 2007; Ratcliffe 2012; Burgess & Moffatt 2011; Humphreys & Eisner 2014; Humphreys et al. 2013; Breen et al. 2011). Attributes include the reported time of occurrence, criminal code, and when available the easting and northing coordinate location of the offence. All liquor and assault incidents with coordinates occurring on Saturday and Sunday morning between 0:00am and 4:59am (n = 1160) were mapped to their address. A portion of the liquor infractions (n = 764), issued as a municipal bylaw infraction, were not geo-located to the street level, and as such were not part of our spatial analysis, but were included in time-series analysis to provide additional insight on proactive policing effects. To protect anonymity, crime data were aggregated to monthly and seasonal frequencies and mapped as cumulative densities, instead of individual events.

On-premises liquor primary alcohol establishments were located using data downloaded from the Ministry of Justice BC Liquor control and licensing branch (<http://www.pssg.gov.bc.ca/lclb/licensed/index.htm>). All liquor licenses addresses for the GEA were geo-located using the Government of British Columbia Geocoder Address List Editor (<http://apps.gov.bc.ca/pub/geocoder/geo/editor/index>) with an average score of 89%. Attributes include the alcohol outlet type and seating capacity for on-premises drinking establishments (restaurants, pubs, hotels, clubs, bars). We selected the liquor primary licenses of on-premises nightclubs, bars, hotels, cabaret, and lounges with late night hours (open to at least midnight). Government liquor license data were cross-referenced with Google search to ensure establishment information was up to date. Our final list included 19 liquor primary establishments seating 4295 patrons at capacity.

4.2.3 Spatial analysis

To understand the spatial dynamic of assaults and liquor infractions within the GEA we stratified offences occurring early morning Saturday and Sunday (0:00h-4:59) between May to September per year (i.e., active patrolling times). We separated assault and liquor infractions to understand if patrolling had a different effect on each crime type. The severity of the crimes differs with assaults involving at least two individuals. Also, a portion of the liquor crimes did not include coordinates and we wanted to make a distinction in data quality.

The density of liquor infractions and assaults were mapped for each year using Kernel Density Estimation (KDE), calculated by the `sm.density` function from `sm` package in R (Bowman & Azzalini 2013). The gradations of the density surfaces were generalized, using the same 25 class choropleth gradation, to protect anonymity of crime data. Kernel density is a non-parametric method that estimates a smoothed probability surface mapping the spatial intensity of crime over space (O’Sullivan & Unwin 2010), calculated as:

$$\lambda(s) = \sum_{i=1}^n \frac{1}{\pi r^2} k\left(\frac{d_{is}}{r}\right)$$

where $\lambda(s)$ is the density at location “s” (the grid cell), r is the bandwidth of the kernel density estimate delineating what points to include in the calculation of the kernel density, i is the weight of each point calculated as a function of k , and k is the kernel density function setting the weight of each point (i) relative to its distance (d_{is}) to the grid cell (s) (i.e., as a ratio between the d_{is} and the bandwidth/radius) (Xie & Yan 2008). We applied a Gaussian kernel and selected a 10m bandwidth (i.e., smoothing parameter), justified by both a calculation of Least Square Cross Validation (`bw.ppl` function in the R `spatstat` package (Baddeley et al. 2016)) and cross-referenced with the `h.select` smoothing function part of the `sm` package in R. Both methods ensure the density estimate is not over smoothed, which would generalize the spatial pattern (Seaman et al. 1999).

To determine if any statistically significant differences between the spatial patterns of geo-located assault and liquor infractions we differenced the 2010 and 2013

KDE surfaces from the 2006 density surface, estimated with the same cell size and bandwidth using the `sm.script(lc_rr)` from `sm` package. The script calculates the difference between the between the square root density estimates (KDE surfaces), enveloping where the standardized differences between the density estimates exceeding two standard deviations from the expected 2006 spatial pattern, calculated as:

$$Change_{i\Delta t} = \frac{\sqrt{\hat{\lambda}_{i,t}} - \sqrt{\hat{\lambda}_{i,t+1}}}{\sqrt{se_t^2 + se_{t+1}^2}}$$

where $\hat{\lambda}_{i,t}$ was the kernel density estimate of crime at each grid cell in year t , (2006) and $\hat{\lambda}_{i,t+1}$ was the KDE estimate at the same grid cell in the following period (2010 or 2013), and se_t and se_{t+1} were the standard errors of the KDE in the baseline 2006 surface and 2010 and 2013 policed years (i.e., the measure of variance of the Gaussian kernel function) (Bowman & Azzalini 1997)).

To establish problem areas (i.e., high crime density) and their proximity (distance) to on-premises establishments we overlaid our 2006, 2010, and 2013 KDE density surfaces of liquor and assaults crimes with alcohol outlet locations and characterized the highest density areas (intensity values above the 95% percentile) relative to prominent alcohol establishments. The top 5% of intensity values were used to delineate hot spots because crimes were highly localized, and the 95th quartile cut off resulted in few (3-6) “hot spot” locations per year and crime type. Proximity was measured from the hot spot centroid to all alcohol outlet licenses. The frequency of nightclubs, lounges, bars, hotels and cabarets relative to the highest and lowest crime density blocks were calculated. The names of establishments within the closest proximity to stable liquor and assault hot spots (across 2006, 2010, and 2013) were noted. The radius of kernel bandwidth selected will affect the spatial size of the crime cluster (O’Sullivan & Unwin 2003), and our proximity (distance) calculations; however, our modest 10m radius and the reoccurrence of crime at the same location minimized the possibility of over generalizing the spatial pattern (combining localized hot spots).

4.2.4 Temporal analysis

To identify the peak occurrence of crime in the GEA and any annual reductions we summarized the frequency of assaults and liquor infractions by hour, weekday, month, and year. To assess the effect of proactive policing within the GEA we stratified offences occurring early morning Saturday and Sunday (0:00h-5:00hr) between May to September (active policing months) in 2006, 2010, and 2013 and calculated the frequency by month and year. Using 2006 expected count we conducted a simple chi-square analysis to determine if a significant difference in the frequency of crime occurred after the active policing months (May-Sept) on Saturday and Sunday morning in 2010 and 2013.

Two GLM poisson regression models were also created to simultaneously account for proactive policing (May to September), monthly and yearly effects on the frequency of Saturday and Sunday early morning assaults and liquor infractions in the GEA. A dummy variable indicating proactive policing months in 2010 and 2013 was included to analyze the significance of increased patrolling in the GEA while simultaneously considering the yearly and monthly fluctuations in the frequency of crime between May and September of 2006, 2010 and 2013; a common method across time-series change analysis in alcohol crime research (Mazerolle et al. 2012; Miller et al. 2012; Vingilis et al. 2006; Evelyn Vingilis et al. 2008; E. Vingilis et al. 2008; Vingilis et al. 2005; Chikritzhs & Stockwell 2006; Duailibi et al. 2007; Kypri et al. 2011). To analyze the performance of our models we predict monthly Saturday and Sunday morning frequencies of crime before and after active policing. Comparing the observed offences to the estimated frequency we calculated the coefficient of determination and average absolute error for both models. As a quasi-control for our change detection, we compared the monthly frequency to criminal offences, not specifically targeted by the entertainment district policing (traffic violations, mischief, and drug, robbery, burglary, and disturbance offences), to indicate if similar trends were present during active policing, which would indicate a natural decrease rather than a change caused by increased police patrolling.

4.3 Results

4.3.1 Change in the spatial patterns of crime in the GEA

The spatial density of geo-located crime from May to September between 0:00h and 5:00am decreased from the 2006 baseline, particularly at the southwest end of the GEA (Figure 4.2). Significant decreases in the spatial density of liquor infractions from 2006 to 2010 were observed where Davie and Helmcken streets intersecting Granville Street (St.). Comparing the 2006 spatial density of liquor infractions to 2013 a significant reduction occurred at the Davie St. and Granville St., and Helmcken St. and Granville St. intersections. There was also a reduction in the amount of infractions on Howe St. and Seymour St. The spatial density has significantly concentrated toward the Granville and Smithe St. intersection at the north-east end of GEA, which has been a consistent spatial trend since 2006 (Figure 4.2).

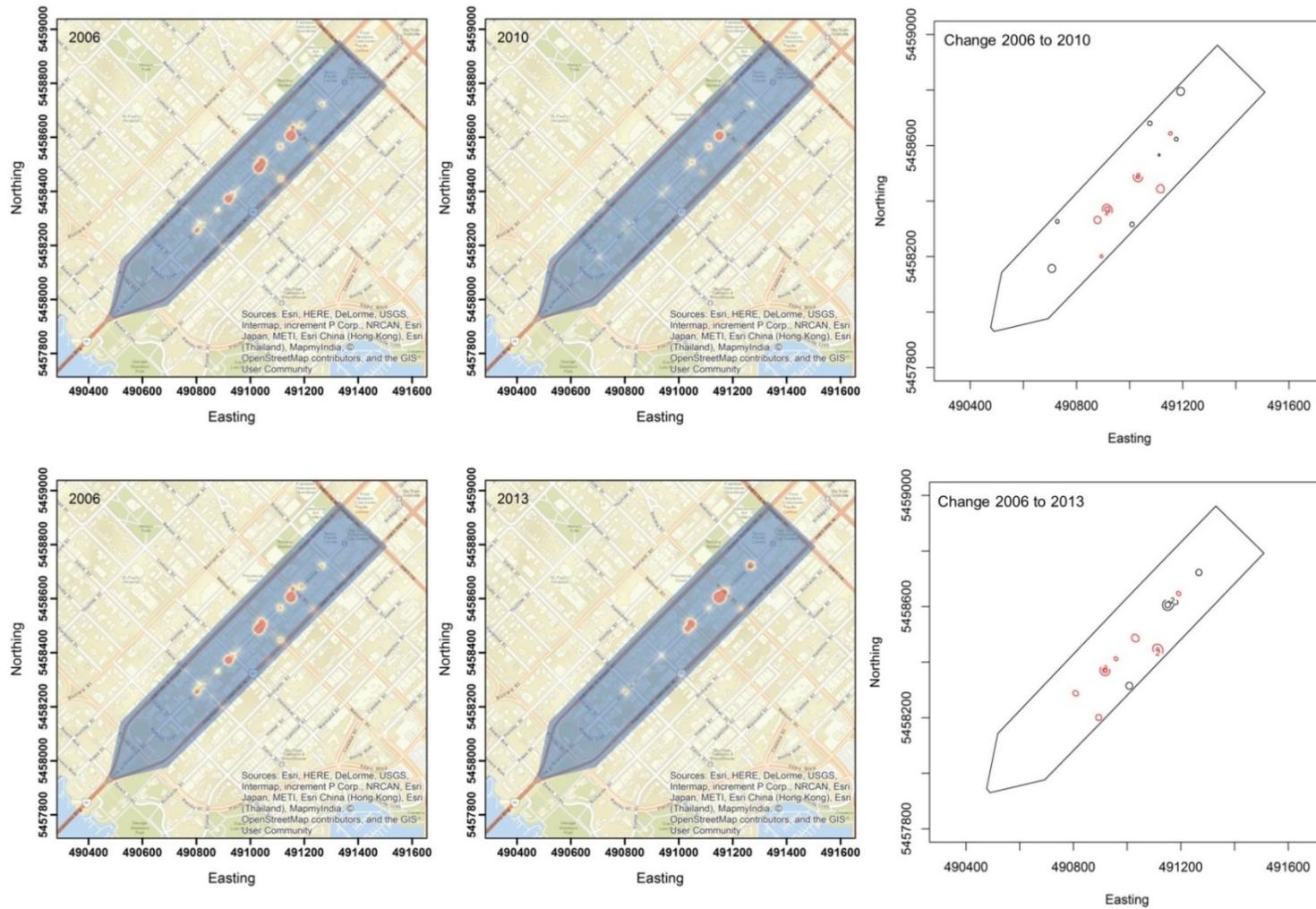


Figure 4.2 displays the change in the spatial density of liquor infractions since 2006. On the left side are the spatial density maps of crime data from 2006 to the change year (2010 and 2013). On the right are the kernel density change maps. Black delineates a two standard deviation increase in spatial density of crime, while red symbolizes a decrease.

The spatial density of geo-located assaults from May to September between 0:00h and 5:00am also decreased in 2010 and 2013 from 2006 baseline density. Between 2006 and 2010 occurrences decreased in the southwest end of the GEA at the intersections of Davie St. and Helmcken St. with Granville St. (Figure 4.3). Comparing the spatial pattern of 2006 to 2013, assaults dispersed across the GEA with notable increase of occurrences on Howe St. (Figure 4.3); however, after reviewing the secondary crime category of these singular events we found the assaults were associated with traffic aggression rather than alcohol consumption on Howe St. Decreases in density occurred at Davie St. and Granville St., Nelson St. and Granville St., and Helmcken St. and Seymour St. (Figure 4.3). Overall the pattern of assaults is less stable than liquor infractions, but shows a trend toward spatial dispersion from Granville St. alcohol outlet strip (Figure 4.3).

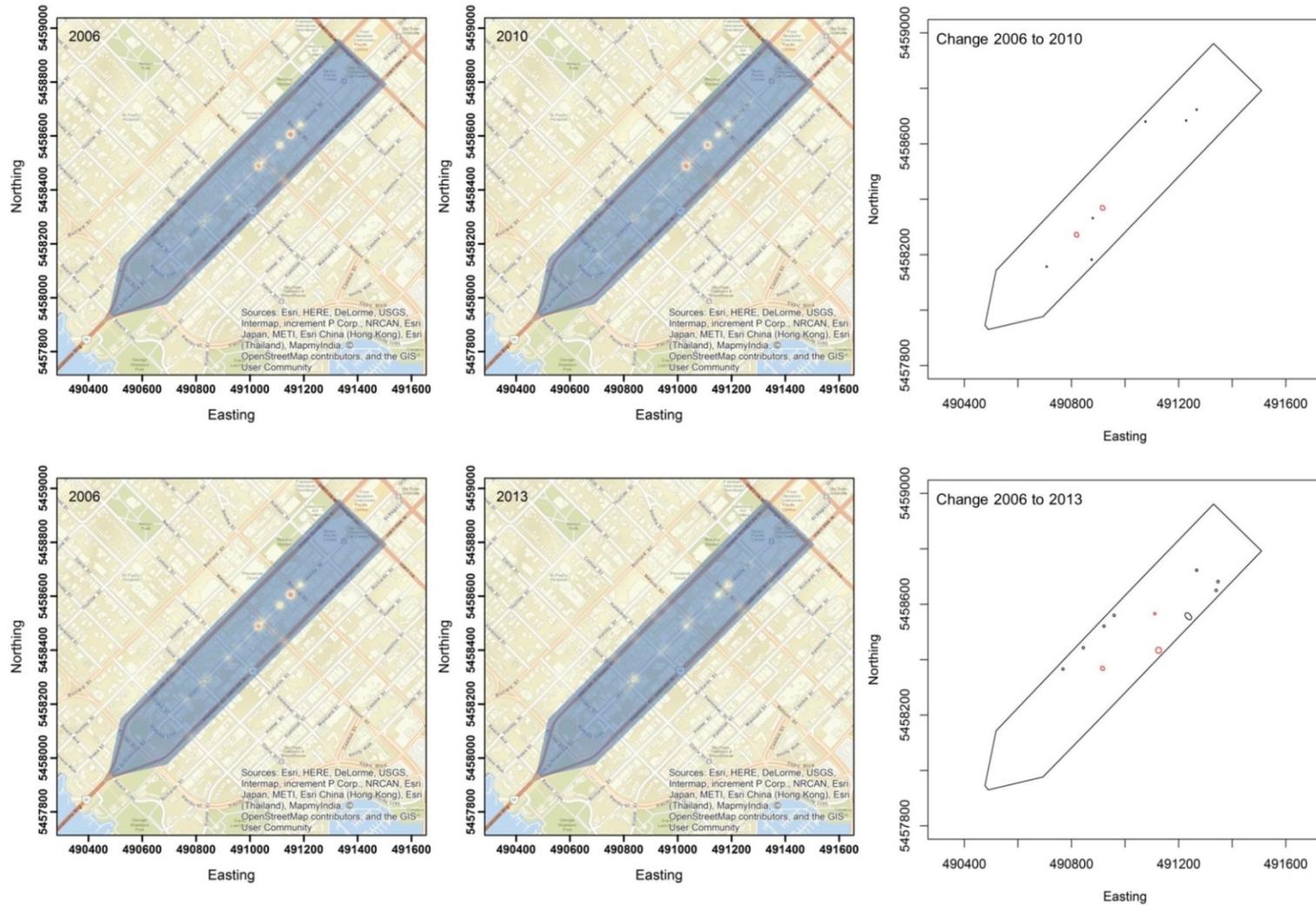


Figure 4.3 displays the change in the spatial density of assaults since 2006. On the left side are the spatial density maps of crime data from 2006 to the change year (2010 and 2013). On the right are the kernel density change maps. Black delineates a two standard deviation increase in spatial density of crime, while red symbolizes a decrease.

Comparing liquor infractions and assaults densities across years (Figure 4.2 & Figure 4.3) the hot spots of infractions have decreased and concentrated north of Helmcken St. with the highest densities remaining around, and north of, the Nelson and Granville St. intersection. Hot spots of both liquor and assaults coincide with locations of nightclubs and strip club along the Granville St. corridor (Figure 4.1, Figure 4.2 & Figure 4.3), with a lower density of crimes south of Helmcken St. in an area with considerably more hotel liquor primary licences (n = 4) than nightclubs (n = 2), Lounges(n = 0), and cabarets (n = 0), compared to the area north that has two bars, two cabarets, one lounge, one strip club, five nightclubs, and one hotel primary licenses. The density of liquor infractions significantly reduced around the Aura and Cabernet nightclubs since 2006, though the areas closest to Venue, Republic, and Caprice nightclubs remain a problem. Assaults have seen the greatest decrease in the density of crimes south of Smithe St. though the density remains in all areas where nightclubs exist (Figure 4.1 & Figure 4.3), with the highest density areas (top 5%) are within 60m of a nightclub. Overall, blocks south of Drake St. and north of Robinson St. have no identifiable hot spots of liquor or assault infractions. These areas also do not have any liquor primary licenses.

4.3.2 Change in the temporal patterns of crime in the GEA

Studying temporal pattern of both geo-located and non-geolocated liquor infractions and assaults both frequencies have decreased in the GEA. Liquor infractions dropped from a total of 1266 infractions in 2006 to 365 in 2013 (71%) and assaults decreased from 225 incidences in 2006 to 168 in 2013 (25%). Both crime types display inconsistent monthly patterns across 2006, 2010, and 2013, with winter Olympics being the likely cause in the spike of liquor and assault crimes of January 2010 (Figure 4.4). Weekday and hourly trends are similar between years and crime types. More than half of liquor infractions (75% (2006), 52% (2010), 72% (2013)) and just above half of assaults occur on Saturday and Sunday morning between 0:00h and 5:00h (52% (2006), 54% (2010), 54% (2013)). Aggregating 2006, 2010, and 2013 data, only 7% of assaults and

liquor infractions occur between 4:00am and 5:00am (Figure 4.5).

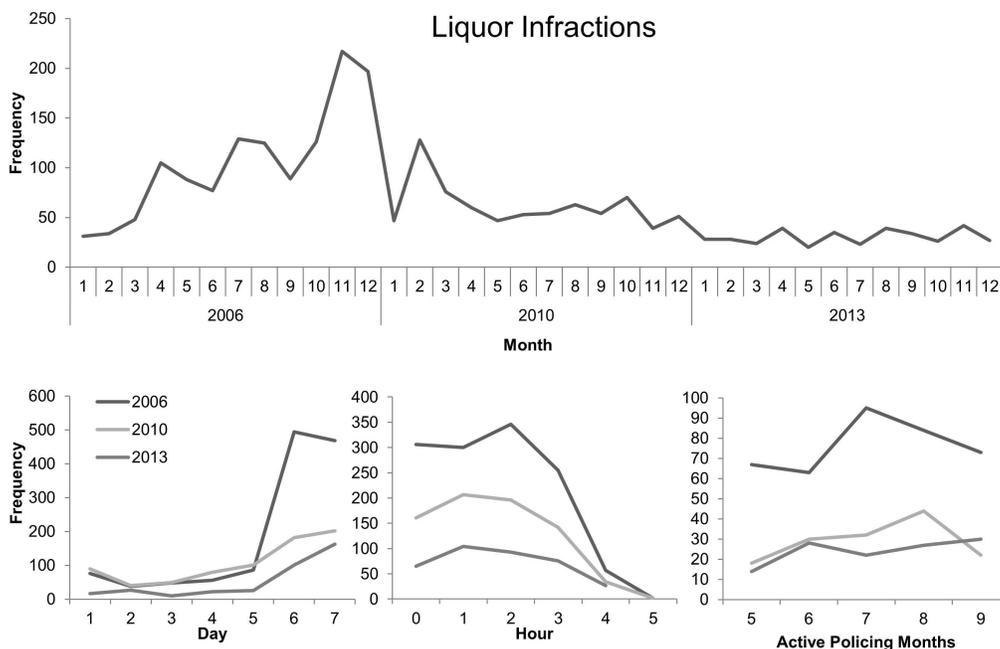


Figure 4.4 displays the temporal pattern of liquor infractions in the GEA. In the daily frequency graph, day 1 is Monday. In the active policing graph the frequency includes infractions occurring early morning Saturday and Sunday between May to September each year.

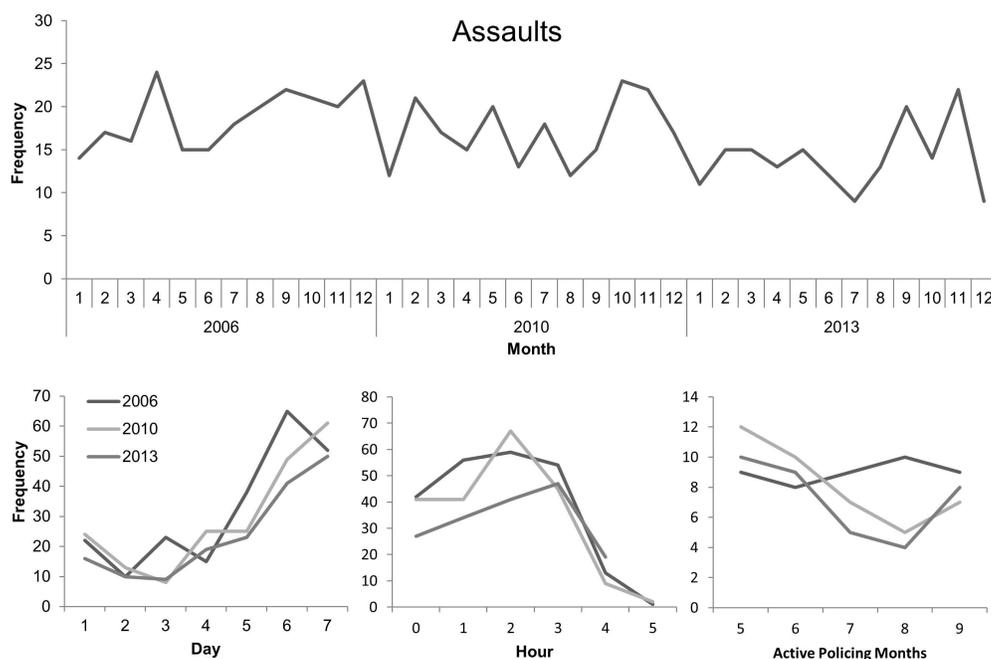


Figure 4.5 displays the temporal pattern of assaults in the GEA. In the daily frequency graph, day 1 is Monday. In the active policing graph the frequency includes infractions occurring early morning Saturday and Sunday between May to September each year.

Stratifying offences to the proactive policing period between May and September before 5:00am our chi-square analysis indicated that both the frequency of liquor infractions and assaults significantly decreased ($P < .05$) after 2006. Liquor infractions dropped from 382 incidences to 145 in 2010 and 121 in 2013. Similarly, assaults significantly decreased from 45 offences in 2006 to 41 in 2010 and 36 in 2013 during the policing period ($p < .05$). Conversely, crimes not directly targeted by the policing campaign rose during the same period from 66 offences in 2006, to 85 in 2010, and 99 in 2013.

Considering yearly and monthly effects on crime frequencies, our Poisson regression models also indicated that proactive policing had a significant effect on liquor infractions ($p < .05$, Table 4.1). Conversely, the impact of proactive policing was inconclusive for assaults ($p > .05$, Table 4.1). Comparing our observed to predict frequencies of crimes our liquor infraction model explained 96% of the variation in offences with a mean absolute error of 5.34 infractions per month (average frequency

liquor infractions was 43 per month). Our assault model explained 57% of the variation in assaults with an average absolute error of 1.29 assaults per month (average frequency was 8 assaults per month), indicating the models were successful capturing the variation of liquor and assault crimes across May to September.

Table 4.1 Poisson GLM modelling results. Policing intervention was a significant factor in the reduction of liquor infractions, but not assaults.

	Liquor			Assaults		
	Estimate	Pr (> z)	Sig. Code	Estimate	Pr (> z)	Sig. Code
Intercept	130.09976	0.11		88.90927	0.56	
Policing Intervention	-0.71139	0.00	***	0.08031	0.85	
July	-0.03948	0.73		0.10008	0.75	
June	-0.24763	0.04	**	0.3514	0.24	
May	-0.44831	0.00	***	0.48955	0.09	
Sept	-0.21511	0.07	*	0.23361	0.44	
Year	-0.06261	0.12		-0.04335	0.56	

Significance codes: 0.001 '***' 0.01 '**' .05 '*' .1 '.'

4.4 Discussion

4.4.1 Active policing effects

It is well known that drinking establishments alter the spatial and temporal pattern of crime. Offences peak during operating hours, and occur in greatest frequency around liquor primary licenses (Fitterer et al. 2015). As such, government officials have used the price of alcohol (e.g., taxes) (Zhao et al. 2013; Stockwell, Zhao, et al. 2012; Stockwell, Auld, et al. 2012), decrease in alcohol licenses (Zhang et al. 2015), staggered closing hours (Humphreys & Eisner 2014; Humphreys et al. 2013; Graham et al. 1998), closing outlets on particular days (Graham et al. 1998), limitations on new liquor licenses (Matthews 2009), and lock-out policies (patrons are no longer readmitted to a drinking establishment after a certain hour) (Miller et al. 2012) to decrease crime. The effects of such alcohol policies vary (Fitterer et al. 2015).

Top-down approaches to alcohol consumption and crime reduction also exist. Safe alcohol serving practices and alcohol access restrictions are promoted by health officials in Canada and Australia (Lang et al. 1998; Go2HR 2015). Police have

implemented bar watch programs (Port Moody Police Department 2016) and active patrolling during on-premises closing times to prevent alcohol-related crime (Matthews 2009). In Victoria, British Columbia police run late-night taxi stands, organizing intoxicated patrons into taxis at the closing of on-premises drinking outlets, to limit hostile interactions between individuals on street corners in the entertainment strip (Downtown Victoria Business Association 2016). Numerous regulations are available to limit alcohol-related crime, identifying effective strategies is essential.

Hot spot policing strategies have reduced various crimes across the United States and Australia (Braga 2005; Braga et al. 2014) by targeting patrols in small areas where crime clusters. A recent review summarising ten randomized control trials and eight quasi-experimental evaluations including 24 tests on the effects of increased policing for crime reduction, reported 20 significant reductions in crime, with a mean effect size of .184 (Braga et al. 2014). Since alcohol policies in British Columbia were liberalized to increase hours of sales, and allow more sales establishments (Government of British Columbia 2015a) police patrolling will be the primary method of limiting alcohol-related crime.

We found that in GEA, moderate patrolling (16 officers) significantly decreased the incidence of liquor infractions by 58% in 2010 and by 69% in 2013 from the baseline frequency in 2006. Similarly, assaults decreased by 16% in 2010 and by 32% in 2013. Areas with the highest (top 5%) of criminal offences were in close proximity to nightclubs (less than 60m), as opposed to any other licensing types, and trended toward the northeast end of GEA after 2006. When analyzed as monthly frequencies proactive policing had no significant effect on monthly assault incidences. Some evaluations of direct patrolling interventions have shown small or non-significant reductions (Sherman et al. 1989; Sviridoff et al. 1992), especially for violent crime in entertainment regions (Frogner et al. 2013). Therefore, our results support existing studies by finding non-significant monthly impacts when the count of assaults were between 4 to 12 occurrences per month with little variance across months (Figure 4.4). Low count and sample size make impacts difficult to detect (Button et al. 2013). Active patrolling is an effective method of reducing crime in the GEA, and if implemented in a targeted structure it may be possible to enhance the effects of the intervention for all crime.

The type of policing and implementation can have a significant effect on the magnitude of the outcome for policing interventions (Durlak & DuPre 2008). The current model presents low intensity and untargeted patrol effort. For example, sixteen officers situate primarily at the entrances of the GEA, in areas exhibiting the lowest intensity of crime (Figure 4.2 & Figure 4.3), to increase the perception of a police presence (Matthews 2009). That leaves 16 foot patrols, to cover a regional area of .3 square kilometres, or rather, an entertainment strip 1.3 kilometres with upwards of six high intensity crime areas (Figure 4.2 & Figure 4.3). If police officers were directed towards these hot spots it would leave approximately two officers to police each hot spot, generally comprising one to two on-premises establishments, exhibiting a relatively small “dosage” effect. Low dosage policing, was indicated as a factor in the small but insignificant effects on patrol interventions (Ratcliffe et al. 2011; Taylor et al. 2011).

Future GEA policing strategies may consider increasing the amount of patrols and target hot spots of crime within the GEA. It is known that guided or problem-oriented policing is more successful than unguided methods of increasing patrols, implementing zero-tolerance policing, and weapon searches to deter crime (Braga et al. 2014). Even if the same numbers of police personnel are used to patrol, efforts should be focus at the north-eastern end of GEA, around nightclubs, during the hours of 1:00am to 3:00am when liquor infractions and violent crimes peak in frequency.

4.4.2 Implications for alcohol policy

In addition to patrolling efforts, our results inform any future alcohol licensing decisions. Municipalities have the burden of alcohol licensing decisions and are expected to assess the risk of crime with each license application in Canada (Matthews 2009; City of Victoria 2012b). It is rare that the intensity of crime is measured in proximity to alcohol establishments (Wilkinson & Livingston 2012; Grubestic & Pridemore 2011), providing little to no evidenced based information for decision making (Fitterer & Nelson 2015; Fitterer et al. 2015). Our results suggest that nightclubs are the highest risk area for crime occurrences, compared to other primary licenses (hotels, pubs). High density crime areas occur no further than 60m from a nightclub in the GEA, and increased in spatial intensity when nightclubs were in close proximity (intersection north of Nelson Street).

Crime also peaked during nightclub primary operating hours (1:00am 3:00am). Therefore, future applications for nightclub licenses should be carefully considered within the context that, any additional license, especially grouping of license, will increase the intensity of crime.

4.4.3 Study considerations

Active policing in the GEA was implemented to appease public concerns for escalating violence, and not as an experiment, a randomized control structure was not implemented. However, no comparable entertainment in Vancouver exists and we excluded winter liquor and assault crimes as a control because policing effort was substantially altered in 2010 for the winter Olympics. In intervention studies it is ideal to use a randomized control structure of police implementation, or have crime statistics from a comparative region, not implementing a police intervention, to use as a control (Braga et al. 2014; Frogner et al. 2013). In lieu, we used untargeted crime in the GEA as comparison data, and found liquor infractions and assaults decreased while other crimes increased during the policing period, indicating that our findings were not the result of a natural decrease in crime.

To protect anonymity, a limited amount of crime data was available. As such we were unable to test if the decrease in crime during the active policing period was anomalous to 2010 and 2013. Data limitations also made it difficult to assess if crime displaced outside of the GEA. Likely foot patrols decreased rather than increased crime in neighbouring areas see (Braga et al. 2014) for meta-analysis. GEA policing is ongoing creating an opportunity to change the implementation of policing to record the timing and location of increase patrols to conduct a quasi-control research design and use data collected outside of the GEA.

4.5 Conclusion

In conclusion, we found that active policing significantly reduced liquor infractions in the GEA and made a small, but non-significant monthly reduction in assaults. All hot spots were located less than 60m from nightclubs. These results indicate

that increasing police presence during high traffic months in entertainment districts can substantively decrease alcohol-attributable crime and should be used as a viable means to protect public safety. Using small scale density mapping and temporal graphing we were able to identify that north-east end of Granville St. had a higher density of liquor infractions, peaking between 1:00am and 3:00am, and should be a target for future policing strategies. In line with previous findings we confirm the influx of crime during the closing hours of on-premises alcohol establishments and show that the spatial arrangement of alcohol-attributable crime matches that of the spatial density of nightclubs, indicating the universal pressure on-premises drinking establishments have on perpetration of crime, and the weight of the decision to allow any new licences. In light of the recent trend to liberalize alcohol access across British Columbia we demonstrated that active police patrolling strategies can reduce the burden of alcohol-attributable crime for society.

5 Chapter 5

Negative Effects of Alcohol Establishment Size and Proximity on the Frequency of Violent and Disorder Crime across Block Groups of Victoria, British Columbia

Abstract

In most areas, greater access to alcohol leads to higher rates of intoxication and subsequent harm, including violent and disorder crimes. Alcohol establishments have been associated with increased crime across multiple regions. However, the combined and different effects of alcohol establishment types, seating capacity, and the distance to other on-premises alcohol establishments on crime rates within a city, at a local scale (i.e., block groups) are not well established. We applied Poisson Generalized Linear Model, with spatial lag variables, to estimate the effects of alcohol establishment's seating capacity (bars, pubs, on-premises) and off-premises licenses on the frequency of violent and disorder crime occurring between 7:00pm and 4:00am Friday and Saturday from January 16th 2015 and May 29th 2016. The model included 138 census Dissemination Areas (block groups) across Victoria, British Columbia (BC). By applying curve fitting and change detection techniques, we also quantified the effects of the distance between bars and pubs on the frequency of crime within 200m of each establishment. Our model explained 76% percent of the variance in violent and disorder crime frequencies. Bars and pubs within block groups, and in neighbouring block groups, had a significant effect ($p < .05$) on the frequency of crime compared to other on-premises licenses (e.g., restaurants, theatres, clubs, hotels) and off-premises liquor stores. Bars and pubs increased violent and disorder crime by a factor of 1.0009 per patron seat. As such, for every additional 1,111 seats the crime frequency per block group is expected to double over a 17 month period. We also found a significant ($p < .05$) drop in the frequency of crime around (200m) bars and pubs that are spaced greater than 300m apart. When bars and pubs are within 300m there were 29 crime incidents over a 17 month period, compared to 2 incidents when establishments were further apart. Overall, our methods provide transferable and quantifiable techniques for predicting the effect of new alcohol establishments, and their placement, on crime, providing evidenced based

information for local governments making alcohol licensing decisions. Our model can be used to predict the expected frequency of crime for additional seating density, and the 300m threshold offers a guideline for locating new liquor establishments in Victoria and other cities.

5.1 Introduction

Greater access to alcohol contributes to higher rates of intoxication, and subsequent harm, including violent (Livingston 2008; Gruenewald et al. 2006; Lipton & Gruenewald 2002; Mazerolle et al. 2012) and disorder crime in particular areas (Donnelly et al. 2006; Kypri et al. 2008; Wechsler et al. 2002; Traci L Toomey et al. 2012; Wilkinson & Livingston 2012; Fitterer et al. 2015). Generally, regions with a greater amount of on (bars, clubs, pubs) and off (liquor store, ubrews) premises alcohol establishments have been linked to the escalation of crime across multiple regions, using various spatial and temporal units of analysis (e.g., census tracts, see (Fitterer et al. 2015; T. L. Toomey et al. 2012) for review). Alcohol consumption and crime is found to peak during the operation of on-premises establishments on weekend nights (Graham et al. 1998; Mazerolle et al. 2012; Kypri et al. 2011; E. Vingilis et al. 2008; Humphreys et al. 2013).

Impaired judgement (Ito et al. 1996) and escalated levels of aggression (Barnwell et al. 2006) while intoxicated likely causes the link between alcohol and crime. As alcohol access increases (more establishments, more patron seats), consumption follows, and the likelihood of crime escalates (Bruun et al. 1975). However, the effects of alcohol establishments on crime are not uniform in all areas. Differences in the effects of on versus off premises alcohol establishments on crime are documented (Pridemore & Grubestic 2012b; White et al. 2015; Conrow et al. 2015; Ratcliffe 2012; Burgess & Moffatt 2011). Bars and pubs located in low guardianship areas (commercial) are theorized to offer a greater opportunity for intoxicated patrons to interact under limited supervision than other on-premises licences or off sales stores. Particular bars are thought to attract risk taking groups, increasing the potential for crime in that area (Gruenewald 2007). On-premises licenses with loud music, dance floors, liberal serving practices, and

high patron capacity are shown to have a disproportionate amount of crime around their establishments (Green & Plant 2007; Newton & Hirschfield 2009; Briscoe & Donnelly 2003).

Currently, what is not well understood are the combined and varying effects of both on-premises establishment types and seating capacities on crime (Fitterer et al. 2015; Fitterer & Nelson 2015; T. L. Toomey et al. 2012; Britt et al. 2005). Many studies combined alcohol license types (on and off) and use large (census tracts, postal codes) regional units to provide information on the association making it hard to distinguish variable establishment effects (Gorman et al., 1998; Gyimah-brempong, 2001; Nielsen, Martinez, & Lee, 2005; Parker et al., 2011; Reid et al., 2003; Resko et al., 2010; Waller et al., 2012; Wheeler & Waller, 2008; Zhu et al., 2004). Other studies separate establishment types, but do not differentiate between establishment size (Lipton & Gruenewald 2002; Gruenewald et al. 2006; Cunradi et al. 2012; Pridemore & Grubestic 2012a; Ratcliffe 2012; Snowden & Pridemore 2013b; Conrow et al. 2015; Crandall et al. 2015; Zhang et al. 2015; Cameron et al. 2015). One study represents on-premises alcohol licenses by size (seats), but it uses a hypothetical change in alcohol establishment locations to indicate rises in crime (Spicer et al. 2012). The effects of proximity between alcohol licences on crime have also not been established.

A small body of literature documents that particular on-premises licenses disproportionately contribute to local crime, in some cases more than 50% (Conrow et al. 2015; Ratcliffe 2012; Burgess & Moffatt 2011; Homel & Clark 1994; Briscoe & Donnelly 2003), and crimes cluster within 152m or 5000ft around establishments (Conrow et al. 2015). Alarming, bars within economically deprived areas can double crime occurrence rates (Gruenewald et al. 2006). In order to reduce alcohol-associated crime, policy makers need consistent evidenced-based information where they can attribute crime to the type, patron capacity, and distance between establishments (factor increase). To date, there has been a lack of crime statistics available at detailed spatial locations (x,y coordinates or blocks), and a limited amount of mapped liquor licenses to test alcohol establishment and crime potential hypothesis in Canada.

The goals of our research were to identify the effects of different licence types and on-premises patrol seat capacity, on the count of violent and disorder crimes in

Victoria, British Columbia block groups (census dissemination areas) using a Poisson Generalized Linear Model (GLM) with spatial effects. Secondly, we quantify the effects of on-premises establishment proximity on the count of crime around establishments using change point analysis. Both objectives provide evidence-based information for establishment size limits and licenses proximity restrictions. Currently, no studies have been published that model the effects of alcohol establishments on crime in Victoria, British Columbia.

5.2 Methods

5.2.1 Study area

Victoria is the capital city of British Columbia, and is located on the southern tip of Vancouver Island. It is world renowned for spectacular gardens and heritage buildings, drawing over three million visitors each year (City of Victoria 2012a). Currently, there are 118 off-premises, and 124 on-premises alcohol establishment licenses within Victoria (Figure 5.1) to serve a metropolitan area of 360,000 people, and a residential population of 80,017 people, according to the 2011 census.

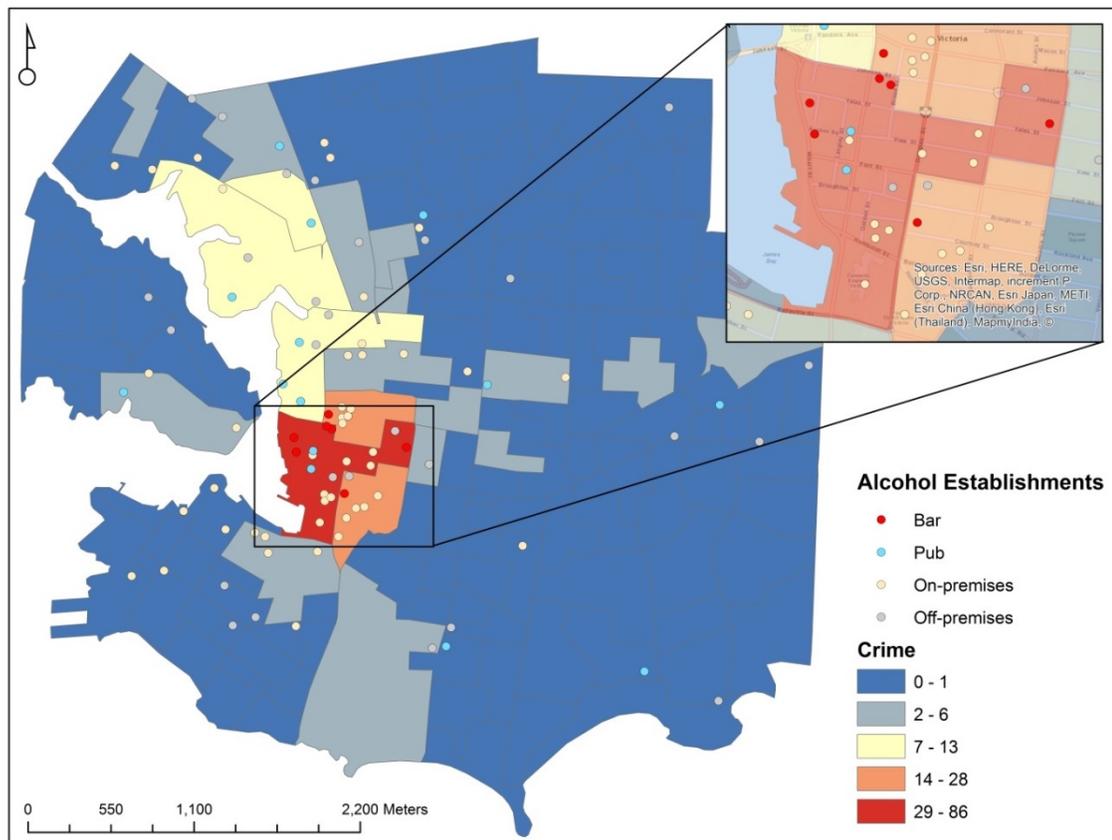


Figure 5.1 Victoria study area displaying the spatial distribution of crime and alcohol establishments. Off-premises licenses include government and independent retail liquor stores, and ubrews. On-premises licenses include establishments where drinking is the primary activity (bars and pubs), and where drinking is a subsidiary activity in restaurants, lounges, theatres, clubs, and hotels (on-premises). For mapping purposes, we differentiated bars as primary drinking establishments with a dance floor.

When making decisions about new liquor licenses (i.e., establishments) it is important to understand the factors that lead to increased risk of crime for the surrounding community and how far these effects extend around the venue (Babor et al. 2010). Currently, no provincial or federal laws are mandated about the allowable density or proximity of establishments in Canada (Giesbrecht et al. 2013). Based on limited amount of evidence-based information municipalities have developed their own policies and restrictions. Municipal governments have set minimum distance allowances of 50 to 500 meters between establishments (Matthews 2009). To assess approvals in Victoria there is an ad hoc 100 to 500 meter radius restriction (land use dependent) around new density liquor licenses (City of Victoria 2012b).

5.2.2 Geographic unit

To estimate the effects of the type of alcohol establishments, and size of on-premises licenses, on violent and disorder crime across Victoria BC we used estimated crime counts and covariate data aggregated to Dissemination Area (DA) units (Table 5.1). DAs are census geographical units composed of small adjacent block groups with a residential population between 400 and 700 persons (Statistics Canada 2009). Victoria is composed of 138 dissemination units with an average footprint of 0.14 km². These units provide a detailed spatial scale for analysis, which include approximately eight blocks in each unit, and accounted for the uncertainty of crime locations along block segments. Since the units are not uniform in shape or size we incorporated the square area as a control variable within our estimation model (Levine et al. 2000).

Table 5.1 Summary of covariates used to model and predict violent and disorder crimes across the 138 dissemination areas

Covariate	Code	Rational
Square meter of each DA	Area	Area accounts for the varying sizes and shapes of DAs.
Count of off-premises licenses per DA	ct_off	Off-premises are hypothesized to attract clientele that may be vulnerable targets of crime, or commit crime around the establishments (Gruenewald 2007; Livingston et al. 2007).
Total patron capacity of bars and pubs per DA	sd_bp	On-premises licenses provide both accesses to alcohol and group at-risk populations together, which can increase the probability of crime within and around these establishments such that intoxication increases aggression, and impairs judgement (Gruenewald 2007; Livingston et al. 2007).
Total patron capacity of bars and pubs in neighboring DAs (lag)	l_sd_bp	
Total patron capacity of hotels, sports clubs, restaurants, theatres, and lounge liquor licenses per DAs (lag)	sd_on	
Total seating capacity of hotels, sports clubs, restaurants, theatres, and lounge liquor licenses in neighbouring DAs (lag)	l_sd_on	
Count of 2011 census population per DA	Pop	Crime is known to occur at a higher frequency in areas with higher population (Hipp & Roussell 2013). We accounted for both residential and dynamic population distributions across DAs.
Count of the closest 2015 bike count collected between 3:00pm and 7:00pm per DA	bike_t	
Count of males between 19 and 24 years old per DA	M1924	Young males are documented and drink a larger amount alcohol than female counterparts (Hughes et al. 2008).
Count of no child households per DA	NoChild	Locations with lower socio-economic status are found to have lower collective efficacy, and therefore crime tends to occur at a higher frequency in these areas. These areas have a perceived lawlessness (broken windows) and inability resist venues that attract crime (alcohol establishments).
Average amount of children per family per DA	AvgChild	
Number other primary languages spoken per DA	Lang	
Count of needle exchanges per DA	Needle	Needle exchanges attract clientele prone to criminal behavior (Petrescu 2016).
Count of lighting structures per DA	Lights	Lighting accounts for conspicuousness of an area and night-time population distribution. A greater amount of lights are needed for a larger population.
Dominant landuse zone per DA	Zone	Industrial and commercial areas influence crime by providing areas with lower “guardianship” (Pridemore & Grubestic 2012a).

5.2.3 Crime

Violent (assaults, and assaults with a deadly weapon) and disorder crime reports were downloaded from the Victoria Police Department website (crimereports.com), and include all incidence reports occurring in the Victoria area between January 16th 2015 and May 29th 2016. We excluded data before 2014, as liquor licensing laws for on-premises establishment changed to increase happy hours (Government of British Columbia 2014). Drink specials offer in limited times of the day are known to increase alcohol-attributable crime (Baldwin et al. 2014). Downloaded offence attributes included: crime type, the probable time of occurrence, date, incident ID, and 100 block address. To flag alcohol-attributable crime we selected assault and disorder crimes occurring between 7:00pm and 4:00am Friday and Saturday night, and counted the frequency of crime over the time period by hour. Multiple studies have suggested stratifying crime reports to strengthen model or analysis results (Chikritzhs & Stockwell 2007; Mazerolle et al. 2012; Livingston 2008; Breen et al. 2011; Ratcliffe 2012; Burgess & Moffatt 2011; Humphreys & Eisner 2014; Humphreys et al. 2013), since consumption increases during the weekend nights (Room et al. 2012). Disorder and assaults were chosen as the focus crime types such that alcohol is known to increase aggression (Barnwell et al. 2006) and cause impaired judgement (Ito et al. 1996) that can lead to violent and disorderly behaviour. Crime occurrences were geo-coded to 100 block address at 98% success rate with average of 97% accuracy. The remaining 4% were manually geo-coded to match street segments using open street map. For modelling, violent and disorder crime points were summarized into a count per DA.

5.2.4 Covariates

5.2.4.1 Liquor licenses

Alcohol establishments locations (x,y coordinates) including on and off premises were downloaded from the Ministry of Justice BC Liquor control and licensing branch (Government of British Columbia 2015c). All addresses were geo-coded with an average match score of 92% and 99% accuracy. Unmatched addresses were manually geo-referenced to address locations using open street map. Outlet density types were

separated into three classes, as previous research documents variable effects by license type (Cunradi et al. 2012; Mair et al. 2013; Gruenewald & Remer 2006; Michael Livingston 2011). We created one category for off-premises licenses that included government and independent retail liquor stores, and brews. On-premises licenses were separated into two categories that distinguished between establishments where drinking is the primary activity (bars and pubs), and where drinking is a subsidiary activity (restaurants, lounges, theatres, clubs, and hotels).

For modelling purposes we counted the amount of off-sale licenses per DA. On-premises licences were counted as the patron seating capacity for bars and pubs, and a second category seat capacity for hotels, sports clubs, theatres and lounges per DA. In addition, we created spatial lagged covariates that counted the total seating capacity of on-premises alcohol establishments from neighbouring DAs. We incorporated adjacent DA units in our lagged spatial counts such that persons drinking in a bar or pub may commit a crime in neighbouring blocks rather than the focal DA (Lipton & Gruenewald 2002). When calculating the lagged covariates we included the seating capacity of alcohol establishments outside of our study area to negate edge effects at the boundary of our study area (Saanich).

5.2.4.2 Place

In order to represent the effects of place-based attributes on crime we mapped needle exchanges. The needle exchange on Pandora St. in the downtown periphery of Victoria is a long standing hot spot of crime (Petrescu 2016). We geo-coded addresses of needle sites provided by the Vancouver Island Health Authority (Vancouver Island Health Authority 2014). Six needle exchanges were geo-located at 100% accuracy, and were counted per DA unit for the estimation model.

5.2.4.3 Population

To control for the increase of crime in highly populated areas (Hipp & Roussell 2013) we used 2011 census information to count the total residential population per DA. A proxy estimate was also used to represent the dynamic population distribution between DAs during the night time hours. Dynamic population estimates are known to shift the hot spots of crime across cities (Malleon & Andresen 2014). We used 2015 bike counts

collected between 3:00pm and 7:00pm by the Capital Regional District to model the portion of the expected population distribution on weekend nights. A large portion of Victoria's population (~10%) commutes using bicycles for transportation, especially the younger demographic (Jestico et al. 2016). The spatial pattern of bike counts correlates with traffic volumes in Victoria (higher density in downtown), but provides temporally continuous source of data compared to 24hr traffic count (see traffic count data (City of Victoria 2015) and bike count maps (Capital Regional District 2015)). Each DA was attributed the closest bike count, signifying a spatial pattern that showed a higher distribution of population in the downtown centre. We also used 2011 census count of males between 19 and 24 years old, and the median age per DA to signify populations at risk of alcohol attributable-crime. Young males are documented to consume more alcohol (Hughes et al. 2008), and have a higher probability of experiencing harms such as violence while intoxicated (Stockwell et al. 1993; Barnwell et al. 2006; Connor et al. 2011; Kraus et al. 2009).

5.2.4.4 Socio-economic

Areas of lower socio-economic status, and higher ethnic diversity moderate the alcohol-crime relationship and tend to experience a greater frequency of crime occurrences (Franklin et al. 2010; Jennings et al. 2013; Liang & Chikritzhs 2011; A. L. Nielsen et al. 2005; Pridemore & Grubestic 2012b). Communities with less capital and collective efficacy are vulnerable to the inclusion of venues (drinking establishments, and needle exchanges) that attract criminal activity in their neighbourhoods (Sampson 1997). A high ethnic diversity may represent a stratified population unable to group against crime (Sampson & Groves 1989). To indicate demographic variance and affluence linked to collective efficacy, we used 2011 census data to count the number of childless households per DA, and average number of children per family per DA. To represent multi-cultural communities we used census information on the amount of other official languages spoken per DA.

5.2.4.5 Structural

Crime occurs more often in commercial and industrial areas where there is a decrease in the amount witnesses (Stucky & Ottensmann 2009), and there is a greater

number of venues that attract crime (e.g. alcohol outlets (Pridemore & Grubestic 2012a)). Structural characteristics of the city were represented with lighting fixtures and zoning information. Using Victoria zoning data from the Victoria Open Data Catalog we stratified zones into five categories (commercial, residential, industrial, service, and other), then mapped the dominant land use category per DA. Using light pole and structure information from the Victoria Open Data Catalog we also counted the amount of light structures per DA to represent night-time visibility, and provide a proxy represents the night-time population distribution.

5.2.5 Spatial Lag Model

To estimate the effects of off-premises establishments and patron seat capacity of on-premises alcohol establishments on violent crime and disorder counts we applied a Poisson Generalized Linear Model with spatial lag effect (Levine et al. 2000). The GLM uses a linear combination of covariates to estimate and predict violent and disorder crime counts. Lag models are an extension of GLMs that include covariates that are spatially structured so that information from neighbouring analysis units are used to predict the focal DA's crime count (Anselin 2009), and have been applied in multiple alcohol establishment-crime studies (e.g., Costanza, William, and Shihadeh 2012; Franklin et al. 2010; Grubestic et al. 2013; Livingston 2008; Pridemore and Grubestic 2012a). We mapped the observed and predicted crime counts per DA using a natural break classification scheme that ensured similarity in crime counts within groups, and largest change in crime counts between. Exponents of the coefficients were calculated to indicate the unit factor increase for each variable.

5.2.6 Model validation

Prior to modelling we produced a Spearman's correlation matrix to ensure independence between our variables. Once estimation was complete, we summarized the predicted errors from our model and calculated a McFadden pseudo r-squared value, recommended for multinomial models, to indicate the variance explained (Veall & Zimmermann 1996). To ensure independence in errors (residuals) between spatial units we ran a lag 1 (adjacent DAs) Moran's I cluster analysis (Dormann et al. 2007). Moran's

I calculates the spatial autocorrelation (similarity in error values between spatial units) across spatial units within a spatial neighbourhood (focal DAs and adjacent DAs). By calculating a global “I” value, we determined if residuals within DAs and adjacent DAs were clustered, and extreme (low, high, low-high, high-low) relative to the mean error (O’Sullivan & Unwin 2010). The “I” value was compared to a spatial pattern of residuals distributed under complete spatial randomness, and it was determined if the pattern was significantly clustered, random, or dispersed. To indicate the fit of our model, we ran a goodness of variance fit test between the model deviance and an “ideal” saturated model where the predicted values are identical to the observed.

5.2.7 Distance modelling

Drawing from change-point time-series modelling and semi-variogram techniques we conducted a hybrid approach to identify if the spacing (distance) between alcohol establishments had a significant effect on violent and disorder crime around establishments. We focused our analysis on bar and pubs, which had significant effect on the frequency of violent and disorder crimes per DA in Victoria ($p < .05$). At the location of each bar and pub we delineated a 200m radius buffer and counted the amount of violent and disorder crime that fell within each establishment buffer. Since each city block was between 150m to 200m long, the 200m buffer represented the 100 block address accuracy of the violent and disorder crime locations. Next we calculated the distance between a bar or pub, and the closest bar or pub to that location. Using a scatter plot we graphed the distance between the establishment and the nearest bar and pub (x-axis), against the count of violent and disorder around (200m) each bar and pub (y-axis). From the relationship, we calculated a distance decay function (curve) to model the expected increase of crime for every meter of distance between alcohol establishments (3rd order polynomial) (Martínez & Viegas 2013). The model fit was evaluated by the R^2 value, and standard error.

To identify a low-risk threshold for the proximity of bars and pubs we applied a change-point analysis on the establishment distance function to determine the threshold at which the count of crime around establishments significantly decreased (software: <http://www.variation.com/cpa/>). Other alcohol-crime research have used change-point

regression to determine the distance at which crime no longer clusters around alcohol establishments (Ratcliffe 2012). Changes in crime frequency with distance between establishments were determined using a cumulative sum method. A significant change was flagged by comparing the cumulative sum of the difference between the crime frequencies at each distance lag compared to the average crime frequency around pubs and bars. Only large changes in crime frequencies with a probability of greater than 99% percent confidence of occurrence were identified. Significance was determined by performing 1000 bootstrap iterations of the crime frequency per establishment without replacement and recalculating the cumulative sum difference (Foffani et al. 2003).

5.3 Results

5.3.1 Crime in Victoria

From January 16th 2015 and May 29th, 91 violent and 158 disorder crimes occurred on Friday and Saturday nights (Figure 5.2). Crime peaked at 2:00pm over Friday and Saturday (Figure 5.3), with the majority of violent and disorder crime located in the one downtown block group that is bordered by Belleville St. and Johnson St. and is south of Douglas St., encompassing the Wharf St. area (Figure 5.1). This block group has the highest density of bars in the area ($n = 5$), compared to all other block groups with a maximum of one bar. The spatial pattern of crime dissipates from downtown centre (Figure 5.2). The disproportionate amount of crime in the downtown area is likely influenced by the greater amount of bars and pubs and population in that area during the evening on the weekend.

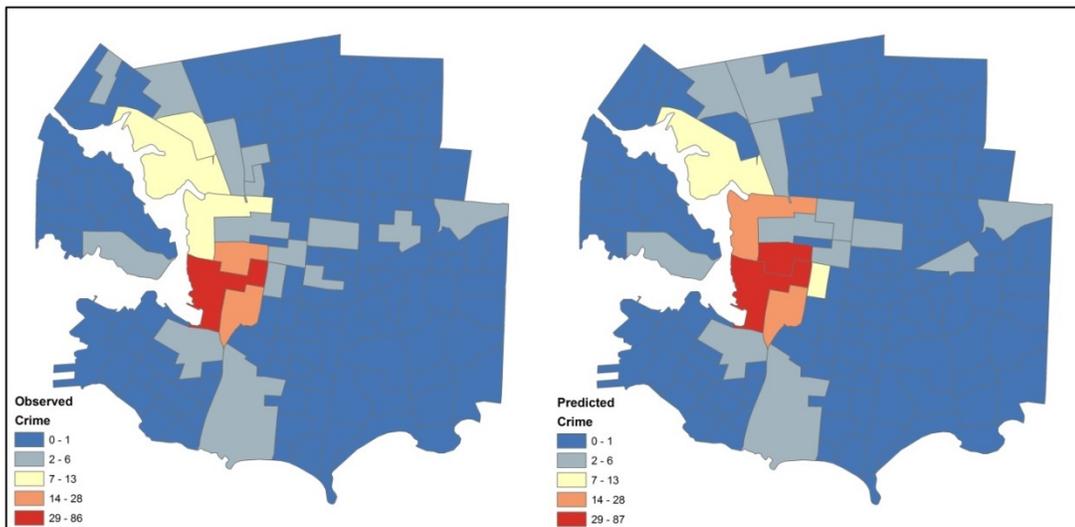


Figure 5.2 Observed and predicted counts of violent and disorder crime reports on Friday and Saturday nights between 7:00pm and 4:00am from January 16th 2015 and May 29th 2016.

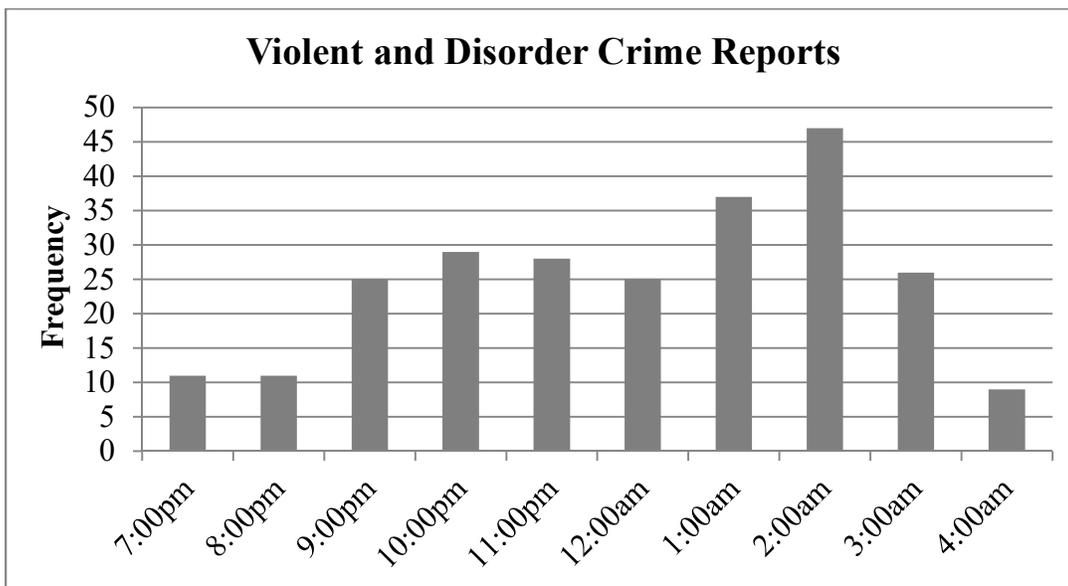


Figure 5.3 Frequency of violent and disorder crime reports between 7:00pm and 4:00am Friday and Saturday night from January 16th 2015 and May 29th 2016.

5.3.2 Model validation results

Our Spearman's rank correlation matrix indicated independence between covariates used to estimate and predict alcohol-associated violent and disorder crimes. The highest correlation coefficient observed was .59 ($p < .05$) between no child households and census total population, all other correlation coefficients were lower than .55, with the majority below .30. The results from our Poisson spatial lag model indicate that 76% of the variation in violent and disorder spatial distribution was explained by alcohol establishments and other covariates. The chi-square goodness of fit test found no significant statistical difference between the deviance of our model and the maximum deviance of the ideal model where there is no difference between observed and predicted values ($p > .05$) indicating a good fit. Model errors had a median of zero a minimum error of -1.3 and a maximum error of 5. Residuals were randomly spatially distributed ($p < .05$), and therefore meet the aspatial and spatial independence criteria.

5.3.3 Estimation results

The seat density of bars and pubs within dissemination areas and in neighbouring areas had a significant positive effect on the count of violent and disorder crimes ($p < .05$, Table 5.2). Bars and pubs were found to increase violent and disorder crime by a factor of 1.0009 per patron seat, so for every additional 1111 seats the crime frequency per block group would double over a 17 month period, holding all other variables constant (the average capacity for a bar or pub in Victoria is 219 patron seats). Bars and pubs in neighbouring communities also increased the frequency of crime violent and disorder by a factor of 1.0007 ($p < .05$). Other significant ($P < .05$) contributing factors included the presence of needle exchange (1.9052), higher total bike commuters (1.0007), lower median age (0.9676), and greater number of spoken languages (1.0099).

Table 5.2 Model estimates, coefficients evaluated at p < .05 level.

Model Results						
	Estimate	Factor	Std. Error	z value	α	Sig. code
(Intercept)	0.6280	1.8739	0.834057	0.753	0.451475	
l_sd_bp	0.0007	1.0007	0.000147	4.943	0.000001	***
Needle	0.6446	1.9052	0.179586	3.589	0.000332	***
Bike_t	0.0007	1.0007	0.000222	3.056	0.002243	**
sd_bp	0.0009	1.0009	0.00048	1.96	0.049971	*
MedAge	-0.0330	0.9676	0.014412	-2.288	0.022145	*
Lang	0.0098	1.0099	0.004939	1.993	0.046208	*
Area	0.0000	1.0000	9.16E-07	2.219	0.02646	*
sd_on	0.0002	1.0002	9.18E-05	1.649	0.099076	
l_sd_on	0.0000	1.0000	2.73E-05	-1.762	0.078098	
ct_off	0.1424	1.1530	0.128672	1.107	0.268411	
M1924	-0.0035	0.9965	0.009972	-0.347	0.728652	
NoChild	0.0052	1.0052	0.005097	1.023	0.306183	
AvgChild	-0.1053	0.9000	0.492014	-0.214	0.830476	
Lights	-0.0023	0.9977	0.001744	-1.317	0.187738	
Zone	-0.1181	0.8886	0.135587	-0.871	0.383619	
Pop	-0.0019	0.9981	0.001425	-1.365	0.172286	

5.3.4 Distance analysis

Distinguishing the effects of bar and pub establishment proximity (x-axis) on crime within 200m of each venue (y-axis) we identified a cubic function (Figure 5.4) as:

$$y = 3.060E+001 - 8.080E-002x + -8.080E-002x^2 + -1.630E-008x^3$$

Crime exponentially increased with the decrease in proximity to other establishments. The fitted curve explains 74% variance in crime frequencies around venues with a standard error of 11.63. Errors were larger at short distance between establishments, indicating a variance in crime around different establishments. Running change detection analysis, we found that overall bars and pubs that were within 300m of each other had significantly more crime than establishments spaced greater than 300m apart ($p < .05$). When bars and pubs are within 300m there were 29 crime incidents over a 17 month period, compared to 2 incidents when establishments were further apart.

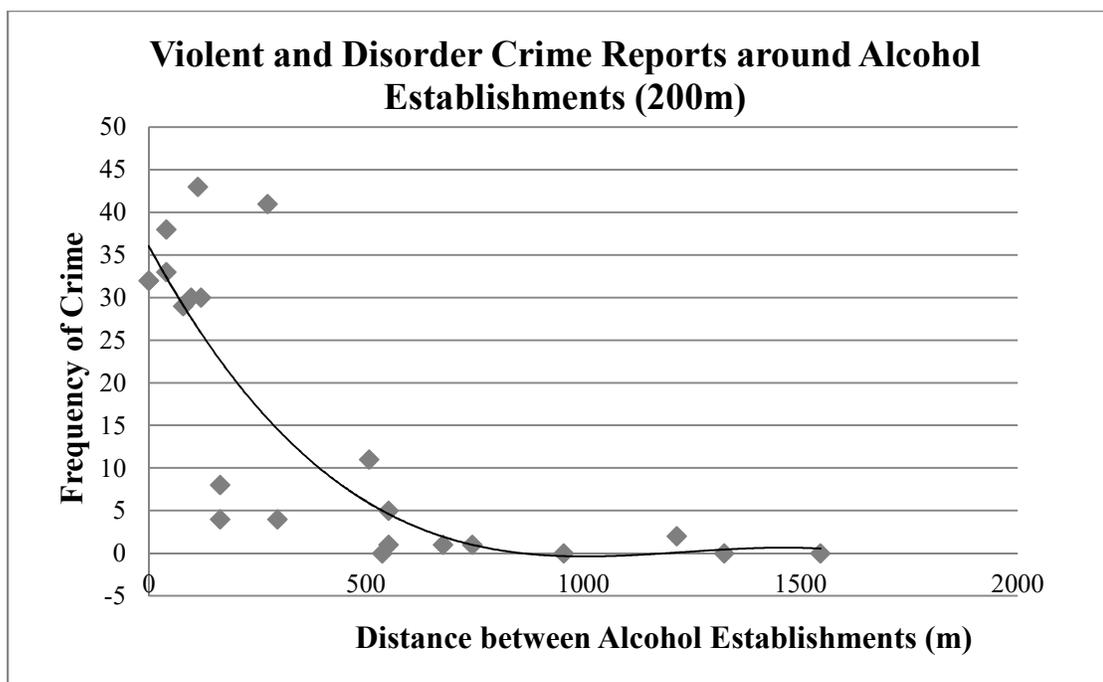


Figure 5.4 Influence of bar and pub proximity (distance in meter) on the frequency of violent and disorder crime around bars and pubs.

5.4 Discussion

Our model contributes a greater level of detail than previous cross-sectional studies quantifying the connection between alcohol establishments and crime over multiple spatial units. While many other studies combined alcohol establishments types, conduct analysis over large spatial units, or count all establishments as having an equal influence on crime (Fitterer et al. 2015; Fitterer & Nelson 2015), we separate establishment categories, represent the variance in establishment size through seating capacity, and consider the spacing of alcohol establishments on crime potential. We provide the first low-risk threshold for allowable seating capacity of on-premises alcohol establishments, and the minimum spacing of venues to reduce alcohol-attributable crime.

By using a smaller spatial unit we were able to distinguish the differences in establishment effects on crime as opposed to larger unit studies can suffer from multicollinearity between alcohol establishment variables. We calculated insignificant ($p > .05$) or low correlation ($< .30$ correlation coefficient) alcohol establishment variables. As

shown in other studies, our results indicate that bars and pubs have a greater factor increase on crime (Lipton & Gruenewald 2002; Gruenewald et al. 2006; Cunradi et al. 2012; Ratcliffe 2012; Snowden & Pridemore 2013b; Conrow et al. 2015; Crandall et al. 2015; Zhang et al. 2015; Cameron et al. 2015). In addition to needle exchanges almost doubling crime counts per DA (Table 5.2), bars and pubs locations within DAs and in neighbouring DAs had a significant effect ($p < .05$) on crime counts. Whereas off-premises licenses and less risk on-premises licenses such as hotels, lounges, theatres, and sports clubs where drinking is not the primary activity had no significant effect.

Accounting for varying sizes of on-premises venues our model provides the expected factor increase in crime for every additional patron seat. The results indicate that an increase of 1,111 seats would double crime rate within a DA, if other environmental factors remained constant. With an average seating capacity of 250, additional 4-5 establishments could double crime in Victoria; therefore, policy officials should be cautious when allocating any new licenses. The addition of any multi-use alcohol establish, such as Victoria's Strathcona Hotel that houses a bar, nightclub, and dance floor with more than 1000 seats would cause a considerable spike (double) in crime.

We established 300m as a low risk threshold for the proximity of establishments, presenting a larger radius than point cluster analysis that identifies crimes to dissipate in intensity around 152m (Conrow et al. 2015). This result expands on the point level crime-establishment studies (White et al. 2015; Conrow et al. 2015; Ratcliffe 2012; Burgess & Moffatt 2011) by quantifying the function between establishment proximity and crime frequency around venues. The equation can be extrapolated to predict how crime will increase over a 17 month period if a new liquor license is situated at a distance between 0 and 1500m from another license.

Our results also support general crime potential theory, asserting that crime is a function of both population and place characteristics across spatial units (Gruenewald et al. 2006). In line with social disorganization theory, and previous alcohol establishment and crime research we found that higher populated areas with lower socio-economic status moderate the crime-alcohol relationship (Gruenewald et al. 2006; Michael Livingston 2011; Waller et al. 2012; McKinney et al. 2009; Gruenewald & Remer 2006;

Treno et al. 2007; Grubestic et al. 2013; Pridemore & Grubestic 2012a). Victoria DAs with lower median age, higher amount of language spoken, and higher total population had a significant effect on the count of violent and disorder reports (Table 5.2). Total commuter count was also a significant predictor of crime compared to census residential population count. This finding continues to support the use of dynamic over residential population counts when predicting crime (Malleeson & Andresen 2014).

We acknowledge some limitations with the present study. Research indicates that crime patterns are generally stable (Weisburd 2015); however, as place-characteristics that link crime to locations change, crime has the potential to shift over space and time. Our model provides a cross-sectional assessment of night-time crime after alcohol policy reform in Victoria British Columbia. To ensure results are robust, future analysis should incorporate data over a longer time-scale and see if the spatial and temporal distribution of crime remains consistent in the downtown core where alcohol establishments are at their highest density to show greater support for the negative effects of on-premises venues on crime. A longer time frame, and therefore larger sample, may allow violent and disorder crimes to be modelled separately, informing alcohol access policy on each.

Our curve fitting procedure also found larger errors in the amount of crime around establishments spaced less than 300m apart (Figure 5.4). Errors indicate that some establishments in the bar and pub category present higher risk for crime potential than others. Studies that address the differences in the characteristics of bars and pubs that have a higher influence on crime are still needed. The quality of establishment distance analysis and modelling could also be improved by a greater accuracy in the location of crime reports. Crime reports were downloaded with a 100 block address limiting placement accuracy and in turn the size of the spatial units we could use for modelling. Since the average 100 block in Victoria is 200m long we were limited in presenting any higher spatial accuracy. If crime were located at the x.y coordinate we could have predicted crime across blocks, and had a greater confidence in allocating crime to each on-premises alcohol establishment when quantifying our low-risk distance threshold between establishments.

5.5 Conclusion

Crime followed an expected pattern where reports of violent and disorder offences peaked during the closing of on-premises locations (2:00am) and downtown blocks had the highest frequency of crime which coincided with the highest number of bars per DA region. Bars and pubs should be the focused locations of risk. Both our spatial lag model and distance analysis found violence and disorder to increase around bars and pubs, especially when spaced less than 300m from each other. In future, policy makers could use our factor coefficients (1.0009 and 1.0007) to calculate the expected increase in crime for proposed licenses in similar sized cities, and apply the 300m distance as a low-risk threshold where crime is expected to exponentially increase if any new liquor establishment are spaced within 300m. Currently Canada has no official density limitations (Giesbrecht et al. 2013), leaving municipal governments to make decisions about the placement of new liquor licenses. Our results offer at a fine level of spatial detail for evidenced-based alcohol license decision making at a time when alcohol policy reform is prioritized by British Columbia government.

6 Chapter 6

6.1 Conclusions

Greater alcohol access contributes to escalated levels of crime including domestic violence (Cunradi et al., 2012; Livingston, 2011; McKinney et al., 2009; Waller et al., 2012), sexual assaults (Schofield & Denson 2013), assaults (Chikritzhs & Stockwell 2002; Mair et al. 2013; Livingston 2008; Lipton & Gruenewald 2002), and disorder (Donnelly et al. 2006; Kypri et al. 2008; Wechsler et al. 2002; Traci L Toomey et al. 2012; Wilkinson & Livingston 2012). The risk of criminal behaviour increases with the frequency and volume of alcohol consumption (Barnwell et al. 2006; Lightowlers et al. 2013; Connor et al. 2011), and certain types of drinking environments and activities (Briscoe and Donnelly, 2003; Chikritzhs and Stockwell, 2002, 2007; Green and Plant, 2007; Hughes et al., 2008, 2011; Livingston et al., 2007; Mazerolle et al., 2012; Newton and Hirschfield, 2009). Researchers continue to report differences in the effects of alcohol access restriction strategies for crime reduction, and the results from various methods used to estimate the association between crime are inconsistent (Fitterer & Nelson 2015; Fitterer et al. 2015). To date, smaller government agencies such as municipalities are relied upon to address the limitations on on-premises alcohol establishments (Matthews 2009); however, there is a limited amount of published evidence to draw evidence-based policy guidelines for local communities.

The primary contributions of this dissertation compose a comprehensive synthesis of successful alcohol access restrictions, and new policy recommendations for crime reduction. Chapters 2 and 3 provide cross-disciplinary policy and methodological reviews that summarize and contrast the effects of alcohol access restrictions (alcohol price, hours of sales, outlet densities) on crime. A critique on the state-of-the-art in statistical methods used to associate crime with alcohol availability was conducted to explain the fragmentation of results across the literature. Key recommendations were to expand the application of spatial statistics to alcohol-attributable crime research to reduce scale effects. Chapters 4 and 5 advance the knowledge of local scale effects of different alcohol establishment types on crime and provide transferable models to estimate the effects of

alcohol establishment seating capacity and proximity between establishments on the frequency of crime.

In more detail, Chapter 2 extends the findings of existing alcohol policy reviews by updating and simultaneously evaluating the effects of alcohol price, hours of sales, and alcohol outlets on violent offences were previous reviews have focused on one (Wagenaar et al. 2010; Stockwell & Chikritzhs 2009) or two (Popova et al., 2009) alcohol access restrictions. By reviewing 87 relevant studies on alcohol access and violence conducted across 12 countries it was recommended that future studies use longitudinal data, place a greater emphasis on validating model, and whenever possible collect the joint distribution between violent crime, intoxication, place in increase and the quality of alcohol-crime studies. Recommendations suggest a greater uptake of local-level analysis to benefit variances in the effects of alcohol establishment's types by relating the location of a crime to establishment proximity. Overall, the syntheses indicated that any restriction in alcohol access would reduce crime. Even minor increases in alcohol price (1%), moderate changes to closing times (1hr), and conservative limits on alcohol establishment densities (<25 outlets per postal code) can have a substantive crime reduction effects.

Chapter 3, aids alcohol and policy crime researchers in the identification of new analysis strategies for the crime-alcohol access research. The methodological review provides the first comprehensive synthesis and critique of existing methods of spatially and quantitatively modelling the effects of alcohol exposure on crime, including 90 publications. Where most comprehensive reviews study the effect of alcohol on the frequency of disease, injury and crime from a harms perspective (Campbell et al., 2009; Gruenewald, 2007; Livingston et al., 2007; Popova et al., 2009; Stockwell & Chikritzhs, 2009; Wagenaar et al., 2010), this review evaluated the suitability of quantitative analysis strategies in regards to the scope, scale, and analytic objectives highlighting methods keenly adapted to spatial effects modelling. Opportunities were identified to use novel sources of spatial data from non-traditional data sources such as social media to study how the size and capacity of drinking establishments impacts alcohol consumption and crime, across space and time. New techniques available for rate calculations across small analysis units were described, and it was anticipated that there would be a surge in the

spatio-temporal analysis of the alcohol consumption and crime connection. With advances in spatial-temporal data collection uptake of flexible Bayesian modelling, the inclusion of spatio-temporal analysis, and predictive modelling over small areas was recommended.

Chapter 4 provides a detailed analysis of how crime clusters in an entertainment district of British Columbia. Since the majority of quantitative alcohol outlet studies crime studies have been conducted analysis over aggregated units such as census tracts and zip codes (Fitterer et al. 2015) the results show a unique point pattern perspective to the distribution of crime over an entertainment district mapping the distributional characteristics of crime and alcohol establishments. By identifying stability in crime hot spots, the results of this research contributed to place theories (Gorman et al. 2013) by indicating that particular establishment types (nightclubs/bars) attract criminal behaviour. While liquor and assault crimes significantly reduced with the creation of an active policing program in the Granville St. entertainment district, hot spots of offences remained within 60m proximity to nightclubs. These results support other literature that indicated bars and nightclubs to have higher risks of nearby crime compared to off sale or on-premises alcohol licenses where drinking is not the primary activity (Lipton & Gruenewald 2002; Gruenewald et al. 2006; Cunradi et al. 2012; Ratcliffe 2012; Snowden & Pridemore 2013b; Conrow et al. 2015; Crandall et al. 2015; Zhang et al. 2015; Cameron et al. 2015). A higher amount of police patrol officers targeted at persistent crime hot spot in the North East side of the Granville St. entertainment district were recommended for crime reduction.

Chapter 5, contributes to the select few studies that model the relationship of alcohol outlet density types and violent crime across small spatial units over city extents (Costanza et al. 2012; Gorman et al. 2001; Pridemore & Grubestic 2012a; Pridemore & Grubestic 2012b; Speer et al. 1998; White et al. 2015; Britt et al. 2005; T. L. Toomey et al. 2012). The results provide the first study to measure the effects of patron seating capacity of on-premises alcohol outlet types on crime in British Columbia (Fitterer & Nelson 2015), and controls for dynamic population effects on crime (Malleeson & Andresen 2014), as opposed to the commonly used census residential estimates (Fitterer & Nelson 2015). These results fill an information gap in the regulation of new on-

premises alcohol establishment developments, providing evidence-based results for setting minimum restrictions on the proximity of on-premises alcohol outlets. Models are transferable and support alcohol policy analysis that needs to quantify the risk of different alcohol licenses in terms of size of the establishment and proximity to other establishments.

Overall, the results of my dissertation respond to the overarching question “how does alcohol access contribute to the frequency of crime?”. Contributing to current policy frameworks, results indicate that regulations on the spacing of alcohol establishments in Victoria and Vancouver should be increased in commercial/urban areas. In Victoria and Vancouver proximity restrictions are lower in urban areas (i.e., downtown) compared to residential zones. For example, in Victoria on-premises drinking establishments are allowed within 100m of each other in the downtown area, but must be spaced at least 500m apart in residential neighbourhoods (City of Victoria 2012b). In contrast, the results showed that establishments spaced closer than 300m in the downtown area had a higher frequency of crime. While residential areas must be protected from problem venues, they also have a higher collective efficacy (ability to come together to oppose change) to reject new development proposals, which affords them a natural protection. As such, stricter regulations on venue spacing in industrial and commercial areas are recommended.

Overall, the results from chapters 2 through 5 support the combined niche marketing and assortative drinking theories proposed by Gruenewald (2007), by displaying that crime clusters closer to nightclubs/bars and pubs than any other license type, but the frequency of crime is not uniform for all establishments. For example, in Chapter 5 we found larger errors in the association between the frequency of crime around bars and pubs when they were spaced less than 300m apart. This means that while a general exponential trend exists between the proximity of bars and pubs and the frequency of crime, some establishments still attract more crime than others. Characterizing the differences that cause variances in crime across the same type of establishments is an important future consideration for policy analysts in British Columbia.

6.2 Key findings for crime reduction

- Policing entertainment districts reduces alcohol-attributable crime
- Police patrols should target nightclub venues between 2:00am and 3:00am
- Seating capacity of bars and pubs should be limited, and a maximum of 1000 seats per establishment should be considered
- Bars and pubs should be spaced greater than 300m apart

6.3 Future research

In my dissertation I present two case studies that offer the first local scale analyses of alcohol establishment and crime relationship in British Columbia. There are opportunities to support the results as the availability of crime data at x,y locations becomes increasingly available. Within the last year the Vancouver Police released crime data on the Vancouver Open Data Catalogue with offset coordinate locations. Open data presents an opportunity to study crime from 2003 to current date, at the block level and minute accuracy, across Vancouver (<http://vancouver.ca/your-government/open-data-catalogue.aspx>). Spatial accuracy is available at the generalized block location, but the crime categories remain generalized to seven categories in which violent crimes are grouped into one category (“offense against a person”) and other liquor specific infractions are not reported, which is unfortunate when studies report differences in the spatial distribution of violent crime with alcohol establishment types and density (e.g., (Pridemore & Grubestic 2011; Grubestic & Pridemore 2011)). The crime reports web map (www.crimereports.com) offers similar crime data availability, in various cities across North America, including Victoria, Duncan, Kamloops and Vancouver. Crime categories are detailed and distinguish between assault types, but data downloads are limited to the last six months. In order to develop a comprehensive analysis of crime and alcohol access across British Columbia major cities researchers will have to build connections with more than 10 municipal police departments and the Federal Royal Mounted Police who collect data in variable formats and require individual data release agreements.

Recent studies have estimated the effects of alcohol access on crime at greater spatial detail, including data aggregated to block groups (Costanza et al. 2012; Pridemore

& Grubestic 2012a; Pridemore & Grubestic 2012b; White et al. 2015; Snowden & Pridemore 2013a; Snowden & Pridemore 2013b) or analyzed with point coordinates (Conrow et al. 2015; Burgess & Moffatt 2011; Ratcliffe 2012). Using units, such as census blocks, may overcome issues of scale where statistical relationships become stronger and more significant as aggregation of data increases (Jelinski & Wu 1996). It is assumed that smaller units are more homogenous and can represent how people interact with their environment; however, some units present logistical difficulties. For example, using a block unit assumes that persons interact more with the persons on streets behind them than persons on the opposite side of the street (Kim 2016). For this reason, we used agglomerated block groups and lags of alcohol outlets in our own analysis (Chapter 5), but new studies are presenting benefits of analysis at the street segment level where crime on either side of the street are represented as the unit (Kim 2016). The benefits could be substantial in the precision of spatial information that can be presented for crime prediction and interaction of people in their environment with alcohol access. Still researchers need to consider how other structural characteristics such as socio-economics and demographics influence alcohol-associated crime. New methods are being proposed to allocate census collected data (e.g., population, income, and ethnic diversity) to the street segment using weighted average criteria (Kim 2016) and could present a future consideration of crime-alcohol access modelling globally and in British Columbia.

Social media and citizen science are other avenues to collect additional indicators of population at risk and socio-demographics for future local scale alcohol-access studies. Social media has been used to collect demographic data to produce new crime rate estimations (Malleon & Andresen 2014); however, there is still concern about the low percentage of people enabling geotags and the ethics of using data for unintended purposes (Zimmer & Proferes 2014). With time, the number of people using location tracking may increase. There is also benefit in using buyer sites to characterize socio-economic environments. For example, people often tag sales of items and or rental of properties to specific locations which could be used a proxy for affluence and population turn over if data are collected by researchers over time. Citizen science mapping also presents an avenue of capturing alcohol-associated crimes not reported to police. Web mapping services could be developed where people map mischief and assault events, not

reported to police, representing another avenue of data collection that links people and their actions in space and time. Researchers have effectively used mapping portals to collect and map risk environments (Robertson et al. 2015; Nelson et al. 2015).

Finally, there are opportunities to improve the measurement of alcohol access for smaller units (local) studies. In Chapter 5 the seating capacity of establishments was used to account for the variance in size of alcohol establishments across units, including lagged measure to account for neighbouring effects of alcohol establishments on focal crime block. Other researchers have proposed gravity models to measure both the concentration of alcohol establishments and the physical proximity of other establishments. Where measurement is a function of the number of outlets, the population in the area, and the street network distance from unit centroid to other outlets (Grubestic et al. 2016). Using gravity modelling in combination with establishment size could greatly benefit small unit studies.

Overall, the new availability in crime data will allow researchers to test the results found between establishment size and type on crime in Victoria, by expanding analysis to other cities in British Columbia. The general block address of the crime data will allow future studies to explore the use of street segments and conduct longitudinal analysis from 2003-2017. The longer time-span presents an opportunity to study the stability of crime hot spots around alcohol establishments through time and space that can be used to identify problem venues. These problem venues can be characterized compared to other venues to inform crime and alcohol policy management.

Bibliography

- De Andrade, D., Homel, R. & Townsley, M., 2016. Trouble in paradise: The crime and health outcomes of the Surfers Paradise licensed venue lockout. *Drug and Alcohol Review*, 36(July 2015), pp.3–9.
- Anselin, L., 1995. Local Indicators of Spatial Association—LISA. *Geographical Analysis*, 27(2), pp.93–115.
- Anselin, L., 2009. Spatial regression. In *The SAGE handbook of spatial analysis*. London: SAGE Publications Ltd., pp. 255–277.
- Anselin, L., 1989. *What is special about spatial data? Alternative perspectives on spatial data analysis* D. A. Griffith, ed., Institute of Mathematical Geography.
- Babor, T.F. et al., 2010. *Alcohol: No Ordinary Commodity: Research and Public Policy: Research and 2nd ed.*, New York: Oxford University Press Inc.
- Baddeley, A., Turner, R. & Ege, R., 2016. Package “spatstat .”
- Baldwin, J.M., Stogner, J.M. & Miller, B.L., 2014. It’s five o’clock somewhere: an examination of the association between happy hour drinking and negative consequences. *Substance abuse treatment, prevention, and policy*, 9(1), p.17.
- Barnwell, S., Borders, A. & Earleywine, M., 2006. Alcohol-Aggression Expectancies and Dispositional Aggression Moderate the Relationship Between Alcohol Consumption and Alcohol-Related Violence. *Aggressive Behaviour*, 32, pp.517–527.
- Biderman, C., Mello, M.P.D. & Schneider, A., 2009. Dry laws and homicides: Evidence from the Sao Paulo Metropolitan area. *The Economic Journal*, 120, pp.157–182.
- Bloomfield, K., Rossow, I. & Norstrom, T., 2009. Changes in alcohol-related harm after alcohol policy changes in Denmark. *European addiction research*, 15(4), pp.224–31.
- Borges, G., Cherpitel, C. & Rosovsky, H., 1998. Male drinking and violence-related injury in the emergency room. *Addiction*, 93(101), pp.103–112.
- Bowman, A. & Azzalini, A., 1997. *Applied Smoothing Techniques for Data Analysis: The kernel Approach.*, Oxford: OUP Oxford, 1997.
- Bowman, A. & Azzalini, A., 2013. Package “sm .” , pp.11–13. Available at: <http://www.stats.gla.ac.uk/~adrian/sm>.

- Braga, A.A., 2005. Hot spots policing and crime prevention: A systematic review of randomized controlled trials. *Journal of Experimental Criminology*, 1(3), pp.317–342.
- Braga, A., Papachristos, A. & Hureau, D., 2014. The Effects of Hot Spots Policing on Crime: An Updated Systematic Review and Meta-Analysis. *Justice Quarterly*, 31(4), pp.633–663.
- Brantingham, P., 1993. Environment, routine, and situation: Toward a pattern of crime. In C. R.V. & M. Felson, eds. *Routine Activity and Rational Choice. Advances in Criminological Theory*. New Jersey: Transaction Publishers, pp. 259–294.
- Breen, C. et al., 2011. Do community characteristics predict alcohol-related crime? *Alcohol and alcoholism (Oxford, Oxfordshire)*, 46(4), pp.464–70.
- Briscoe, S. & Donnelly, N., 2003. Problematic Licensed Premises for Assault in Inner Sydney, Newcastle and Wollongong. *Australian and New Zealand Journal of Criminology*, 36(1), pp.18–33.
- Britt, R.H. et al., 2005. Neighborhood Level Spatial Analysis of the Relationship Between Alcohol Outlet Density and Criminal Violence. *Environmental and Ecological Statistics*, 12(4), pp.411–426.
- Bromley, R.D.F. & Nelson, A.L., 2002. Alcohol-related crime and disorder across urban space and time: Evidence from a British city. *Geoforum*, 33(2), pp.239–254.
- Brower, A.M. & Carroll, L., 2002. Spatial and temporal aspects of alcohol-related crime in a college town. *Journal of American college health : J of ACH*, 55(5), pp.267–75.
- Bruun, E.K. et al., 1975. *Alcohol Control Policies in Public Health Perspective*, Helsinki: The Finnish Foundation of Alcohol Studies, Vol. 25.
- Burgess, M. & Moffatt, S., 2011. The association between alcohol outlet density and assaults on and around licensed premises. *Crime and Justice Bulletin: Contemporary Issues in Criminal Justice*, 2011(147), pp.1–16.
- Burke, J.G. et al., 2005. An introduction to concept mapping as a participatory public health research method. *Qualitative health research*, 15(10), pp.1392–410.
- Button, K.S. et al., 2013. Power failure: why small sample size undermines the reliability of neuroscience. *Nature reviews. Neuroscience*, 14(5), pp.365–76.
- Cameron, M.P. et al., 2015. Alcohol outlet density and violence: A geographically

- weighted regression approach. *Drug and Alcohol Review*, <http://doi.wiley.com/10.1111/dar.12295>.
- Campbell, C.A. et al., 2009. The effectiveness of limiting alcohol outlet density as a means of reducing excessive alcohol consumption and alcohol-related harms. *American journal of preventive medicine*, 37(6), pp.556–69.
- Capital Regional District, 2015. Regional Cycling Counts. Available at: <https://www.crd.bc.ca/about/data/bike-counts>.
- Cargo, M. & Mercer, S.L., 2008. The value and challenges of participatory research: strengthening its practice. *Annual review of public health*, 29, pp.325–50.
- Cheng, T. et al., 2014. A Dynamic Spatial Weight Matrix and Localized Space-Time Autoregressive Integrated Moving Average for Network Modeling. *Geographical Analysis*, 46(1), pp.75–97.
- Chikritzhs, T. & Stockwell, T., 2002. The impact of later trading hours for Australian public houses (hotels) on levels of violence. *Journal of studies on alcohol*, 63(5), pp.591–9.
- Chikritzhs, T. & Stockwell, T., 2007. The impact of later trading hours for hotels (public houses) on breath alcohol levels of apprehended impaired drivers. *Addiction (Abingdon, England)*, 102(10), pp.1609–17.
- Chikritzhs, T. & Stockwell, T., 2006. The impact of later trading hours for hotels on levels of impaired driver road crashes and driver breath alcohol levels. *Addiction (Abingdon, England)*, 101(9), pp.1254–64.
- City of Victoria, 2012a. About Victoria. Available at: <http://www.victoria.ca/EN/main/community/about.html>.
- City of Victoria, 2012b. City Liquor Licensing Policy & Process. Available from <http://www.victoria.ca/EN/main/departments/legislative-services/liquor-licensing/policy-process.html>.
- City of Victoria, 2015. Traffic Volume (24hr count). *Victoria Open Data Catalogue*. Available at: <http://www.victoria.ca/EN/main/city/open-data-catalogue.html>.
- Clark, T.S. & Linzer, D. a, 2012. Should I Use Fixed or Random Effects? *Mimeo*, pp.1–34.
- Cliff, A.D. & Ord, J.K., 1981. *Spatial Processes: Models and Applications*, London:

Pion.

- Connor, J.L. et al., 2011. Alcohol outlet density, levels of drinking and alcohol-related harm in New Zealand: a national study. *Journal of epidemiology and community health*, 65(10), pp.841–6.
- Conrow, L., Aldstadt, J. & Mendoza, N.S., 2015. A spatio-temporal analysis of on-premises alcohol outlets and violent crime events in Buffalo, NY. *Applied Geography*, 58, pp.198–205.
- Cook, P.J. & Durrance, C.P., 2013. The virtuous tax: lifesaving and crime-prevention effects of the 1991 federal alcohol-tax increase. *Journal of health economics*, 32(1), pp.261–7.
- Costanza, S.E., William, B. & Shihadeh, E., 2012. Alcohol availability and violent crime rates: a spatial analysis. *Journal of Crime and Justice*, 24(1), pp.71–83.
- Crandall, M. et al., 2015. Geographic association of liquor licenses and gunshot wounds in Chicago. *The American Journal of Surgery*, 210(1), pp.99–105.
- Crombie, I.K. et al., 2007. How do public health policies tackle alcohol-related harm: a review of 12 developed countries. *Alcohol and alcoholism (Oxford, Oxfordshire)*, 42(5), pp.492–9.
- Cunradi, C.B. et al., 2012. Alcohol outlet density and intimate partner violence-related emergency department visits. *Alcoholism, clinical and experimental research*, 36(5), pp.847–53.
- Cunradi, C.B. et al., 2011. Alcohol outlets, neighborhood characteristics, and intimate partner violence: ecological analysis of a California city. *Journal of urban health : bulletin of the New York Academy of Medicine*, 88(2), pp.191–200.
- Day, P. et al., 2012. Close proximity to alcohol outlets is associated with increased serious violent crime in New Zealand. *Australian and New Zealand journal of public health*, 36(1), pp.48–54.
- De'ath, G. & Fabricius, K.E., 2000. Classification and Regression Trees: A Powerful Yet Simple Technique for Ecological Data Analysis. *Ecology*, 81(11), pp.3178–3192.
- Diggle, P.J., 2013. *Statistical Analysis of Spatial and Spatio-Temporal Point Patterns* Third., Chapman and Hall.
- Dobson, J.E. et al., 2000. LandScan: A Global Population Database for Estimating

- Populations at Risk. , 66(7), pp.849–857.
- Donnelly, N. et al., 2006. Liquor outlet concentrations and alcohol-related neighbourhood problems. *Bureau of Crime Statistics: Alcohol Studies Bulletin*, 8, pp.1–16.
- Dormann, C. et al., 2007. Methods to account for spatial autocorrelation in the analysis of species distributional data: a review. *Ecography*, 30(5), pp.609–628.
- Douglas, M., 1998. Restriction of the hours of sale of alcohol in a small community: a beneficial impact. *Australian and New Zealand journal of public health*, 22(6), pp.714–9.
- Downtown Victoria Business Association, 2016. After Hours Transport. Available at: <http://downtownvictoria.ca/getting-around/After-Hours>.
- Duailibi, S. et al., 2007. The effect of restricting opening hours on alcohol-related violence. *American journal of public health*, 97(12), pp.2276–80.
- Duke, A.A. et al., 2011. Alcohol dose and aggression: another reason why drinking more is a bad idea. *Journal of studies on alcohol and drugs*, 72(1), pp.34–43.
- Durlak, J.A. & DuPre, E.P., 2008. Implementation matters: A review of research on the influence of implementation on program outcomes and the factors affecting implementation. *American Journal of Community Psychology*, 41(3–4), pp.327–350.
- Durrance, C.P. et al., 2011. Taxing sin and saving lives: Can alcohol taxation reduce female homicides? *Social science & medicine (1982)*, 73(1), pp.169–76.
- El-Maaytah, M. et al., 2008. The effect of the new “24 hour alcohol licensing law” on the incidence of facial trauma in London. *The British journal of oral & maxillofacial surgery*, 46(6), pp.460–3.
- Elhorst, J.P., Wheeler, D.C. & Páez, A., 2010. *Handbook of Applied Spatial Analysis* M. M. Fischer & A. Getis, eds., Berlin, Heidelberg: Springer Berlin Heidelberg.
- Erickson, D.J. et al., 2013. Do Neighborhood Attributes Moderate the Relationship between Alcohol Establishment Density and Crime? *Prevention science : the official journal of the Society for Prevention Research*. Available at: <http://www.ncbi.nlm.nih.gov/pubmed/24337980>.
- Exum, M.L., 2006. Alcohol and aggression: An integration of findings from experimental studies. *Journal of Criminal Justice*, 34(2), pp.131–145.
- Felson, R., Teasdale, B. & Burchfield, K., 2008. The influence of being under the

- influence. *Journal of Research in Crime & Delinquency*, 45(1997), pp.119–141.
- Felson, R.B. & Staff, J., 2010. The Effects of Alcohol Intoxication on Violent Versus Other Offending. *Criminal Justice and Behavior*, 37(12), pp.1343–1360.
- Fitterer, J.L., 2013. Alcohol-Attributable Crimes in BC. *Centre for Addictions Research of BC*. Available at:
<http://www.carbc.ca/Portals/0/propertyagent/558/files/341/alcoholcrime.pdf>.
- Fitterer, J.L. & Nelson, T.A., 2015. A Review of the Statistical and Quantitative Methods Used to Study Alcohol-Attributable Crime. *Plos One*, 10(9), p.e0139344.
- Fitterer, J.L., Nelson, T.A. & Stockwell, T., 2015. A Review of Existing Studies Reporting the Negative Effects of Alcohol Access and Positive Effects of Alcohol Control Policies on Interpersonal Violence. *Frontiers in Public Health*, 3(November), pp.1–11.
- Foffani, G. et al., 2003. 300-Hz subthalamic oscillations in Parkinson's disease. *Brain*, 126(10), pp.2153–2163.
- Fogarty, J., 2006. The nature of the demand for alcohol: understanding elasticity. *British Food Journal*, 108(4), pp.316–332.
- Fotheringham, A.S., 2009. Geographically weighted regression. In A. Stewart Fotheringham & P. A. Rogerson, eds. *The SAGE handbook of spatial analysis*. London: SAGE Publications, pp. 243–255.
- Franklin, F.A. et al., 2010. Alcohol outlets and violent crime in washington d.C. *The western journal of emergency medicine*, 11(3), pp.283–90.
- Freisthler, B., 2004. A spatial analysis of social disorganization, alcohol access, and rates of child maltreatment in neighborhoods. *Children and Youth Services Review*, 26(9), pp.803–819.
- Freisthler, B. & Maguire-Jack, K., 2015. Understanding the Interplay Between Neighborhood Structural Factors, Social Processes, and Alcohol Outlets on Child Physical Abuse. *Child Maltreatment*, Available at:
<http://cmx.sagepub.com/cgi/doi/10.1177/1077559515598000>.
- Freisthler, B., Midanik, L.T. & Gruenewald, P.J., 2004. Alcohol outlets and child physical abuse and neglect: applying routine activities theory to the study of child maltreatment. *Journal of studies on alcohol*, 65(5), pp.586–92.

- Friedman, J.H. & Meulman, J.J., 2003. Multiple additive regression trees with application in epidemiology. *Statistics in medicine*, 22(9), pp.1365–81.
- Frogner, L. et al., 2013. Directed Patrol for Preventing City Centre Street Violence in Sweden - A Hot Spot Policing Intervention. *European Journal on Criminal Policy and Research*, 19(4), pp.333–350.
- Gallet, C.A., 2007. The demand for alcohol: a meta-analysis of elasticities. *The Australian Journal of Agricultural and Resource Economics*, 51(2), pp.121–135.
- Garson, G., 2013. Fundamentals of hierarchical linear and multilevel modeling. *Hierarchical linear modeling: Guide and applications.*, pp.3–25.
- Gerber, M.S., 2014. Predicting crime using Twitter and kernel density estimation. *Decision Support Systems*, 61(1), pp.115–125.
- Gerson, L.W. & Preston, D. a, 1979. Alcohol consumption and the incidence of violent crime. *Journal of studies on alcohol*, 40(3), pp.307–12.
- Giesbrecht, N. et al., 2011. Analysis Alcohol in Canada : reducing the toll through focused. *Canadian Medical Association*, 183(4), pp.450–456.
- Giesbrecht, N., 2006. Alcohol policy in Canada: reflections on the role of the alcohol industry. *Nordic Studies on Alcohol and Drugs*, 23, pp.445–466.
- Giesbrecht, N. et al., 2013. *Strategies to Reduce Alcohol -Related Harms and Costs in Canada: A Comparison of Provincial Policies*, Toronto. Available at: <http://www.carbc.ca/Portals/0/PropertyAgent/558/Files/314/Strategies to Reduce Alcohol Related Harms and Costs 2013.pdf>.
- Go2HR, 2015. Serving it Right: BC's Responsible Beverage Service Program. *go2HR*. Available at: <http://www.servingitright.com/>.
- Gorman, D.M., Labouvie, E.W., et al., 1998. Alcohol availability and domestic violence. *The American journal of drug and alcohol abuse*, 24(4), pp.661–73.
- Gorman, D.M., Speer, P.W., et al., 1998. Risk of assaultive violence and alcohol availability in New Jersey. *American journal of public health*, 88(1), pp.97–100.
- Gorman, D.M. et al., 2001. Spatial Dynamics of Alcohol Availability , Neighborhood Structure and Violent Crime. *Journal of Studies on Alcohol*, 62(September), pp.628–636.
- Gorman, D.M., Gruenewald, P.J. & Waller, L.A., 2013. Linking Places to Problems:

- Geospatial Theories of Neighborhoods, Alcohol and Crime. *GeoJournal*, 78(3), pp.417–428.
- Gorman, D.M., Zhu, L. & Horel, S., 2005. Drug “hot-spots”, alcohol availability and violence. *Drug and alcohol review*, 24(6), pp.507–13.
- Government of British Columbia, 2015a. Factsheet: Liquor law changes benefit British Columbians, industry. Available at: <https://news.gov.bc.ca/factsheets/factsheet-liquor-law-changes-benefit-british-columbians-industry>.
- Government of British Columbia, 2015b. Factsheet: Liquor law changes benefit British Columbias, industry. *BC Gov News*. Available at: <https://news.gov.bc.ca/factsheets/factsheet-liquor-law-changes-benefit-british-columbians-industry>.
- Government of British Columbia, 2014. Happy hours and minimum pricing take effect in B.C. *BC Gov News*. Available at: <https://news.gov.bc.ca/stories/happy-hours-and-minimum-pricing-take-effect-in-bc>.
- Government of British Columbia, 2015c. Licensed Establishment Locations. Available at: <http://www.pssg.gov.bc.ca/lclb/licensed/index.htm>.
- Graham, C.A., McLeod, L.S. & Steedman, D.J., 1998. Restricting extensions to permitted licensing hours does not influence the numbers of alcohol or assault related attendances at an inner city accident and emergency department. *Journal of accident & emergency medicine*, 15(1), pp.23–5.
- Graham, K. et al., 2006. Bad nights or bad bars? Multi-level analysis of environmental predictors of aggression in late-night large-capacity bars and clubs. *Addiction*, 101(11), pp.1569–80.
- Green, J. & Plant, M.A., 2007. *Bad bars: A review of risk factors*, Available at: <http://informahealthcare.com/doi/abs/10.1080/14659890701374703>.
- Grubestic, T.H. et al., 2013. Alcohol outlet density and violence: the role of risky retailers and alcohol-related expenditures. *Alcohol and alcoholism (Oxford, Oxfordshire)*, 48(5), pp.613–9.
- Grubestic, T.H. et al., 2016. Comparative approaches for assessing access to alcohol outlets: exploring the utility of a gravity potential approach. *Population Health Metrics*, 14(1), p.25.

- Grubestic, T.H., Mack, E. a & Kaylen, M.T., 2012. Comparative modeling approaches for understanding urban violence. *Social science research*, 41(1), pp.92–109.
- Grubestic, T.H. & Pridemore, W.A., 2011. Alcohol outlets and clusters of violence. *International journal of health geographics*, 10(30), pp.1–12.
- Gruenewald, P.J. et al., 2006. Ecological models of alcohol outlets and violent assaults: crime potentials and geospatial analysis. *Addiction (Abingdon, England)*, 101(5), pp.666–77.
- Gruenewald, P.J. et al., 1996. The geography of availability and driving after drinking. *Addiction (Abingdon, England)*, 91(7), pp.967–83.
- Gruenewald, P.J., 2007. The spatial ecology of alcohol problems: niche theory and assortative drinking. *Addiction (Abingdon, England)*, 102(6), pp.870–8.
- Gruenewald, P.J., Johnson, F.W. & Treno, A.J., 2002. Outlets, drinking and driving: a multilevel analysis of availability. *Journal of studies on alcohol*, 63(4), pp.460–8.
- Gruenewald, P.J., Ponicki, W.R. & Holder, H.D., 1993. The Relationship of Outlet Densities to Alcohol Consumption: A Time Series Cross-Sectional Analysis. *Alcoholism, clinical and experimental research*, 17(1), pp.38–47.
- Gruenewald, P.J. & Remer, L., 2006. Changes in outlet densities affect violence rates. *Alcoholism, clinical and experimental research*, 30(7), pp.1184–93.
- Gustafsson, N.J. & Ramstedt, M.R., 2011. Changes in alcohol-related harm in Sweden after increasing alcohol import quotas and a Danish tax decrease--an interrupted time-series analysis for 2000-2007. *International journal of epidemiology*, 40(2), pp.432–40.
- Gyimah-brempong, K., 2001. Alcohol Availability and Crime : Evidence from Census Tract Data. *Southern Economic Journal*, 68(1), pp.2–21.
- Han, D. & Gorman, D.M., 2013. Evaluating the effects of the introduction of off-sale alcohol outlets on violent crime. *Alcohol and alcoholism (Oxford, Oxfordshire)*, 48(3), pp.370–4.
- Herttua, K. et al., 2008. The impact of a large reduction in the price of alcohol on area differences in interpersonal violence: a natural experiment based on aggregate data. *Journal of epidemiology and community health*, 62(11), pp.995–1001.
- Hipp, J.R. & Roussell, A., 2013. Micro- and Macro-Environment Population and the

- Consequences for Crime Rates. , 0(0), pp.1–33.
- Homel, R. & Clark, J., 1994. The prediction and prevention of Violence in Pubs and Clubs. *Crime Prevention Studies*, 3, pp.1–46.
- Hughes, K. et al., 2008. Alcohol, nightlife and violence: the relative contributions of drinking before and during nights out to negative health and criminal justice outcomes. *Addiction (Abingdon, England)*, 103(1), pp.60–5.
- Hughes, K. et al., 2011. Environmental factors in drinking venues and alcohol-related harm: the evidence base for European intervention. *Addiction (Abingdon, England)*, 106 Suppl, pp.37–46.
- Humphreys, D.K. & Eisner, M.P., 2014. Do flexible alcohol trading hours reduce violence? A theory-based natural experiment in alcohol policy. *Social Science & Medicine*, 102, pp.1–9.
- Humphreys, D.K., Eisner, M.P. & Wiebe, D.J., 2013. Evaluating the impact of flexible alcohol trading hours on violence: an interrupted time series analysis. *PloS one*, 8(2), p.e55581.
- Iritani, B.J. et al., 2013. Alcohol Outlet Density and Young Women’s Perpetration of Violence Toward Male Intimate Partners. *Journal of family violence*, 28(5), pp.459–470.
- Ito, T.A. et al., 1996. Alcohol and Aggression : A Meta-Analysis on the Moderating Effects of Inhibitory Cues , Triggering Events, and Self-Focused Attention. *American Psychological Association*, 120(1), pp.60–82.
- Jackson, C.K. & Owens, E.G., 2011. One for the road: Public transportation, alcohol consumption, and intoxicated driving. *Journal of Public Economics*, 95(1–2), pp.106–121.
- Jelinski, D.E. & Wu, J., 1996. The modifiable areal unit problem and implications for landscape ecology. *Landscape Ecology*, 11(3), pp.129–140.
- Jennings, J.M. et al., 2013. Neighborhood Alcohol Outlets and the Association with Violent Crime in One Mid-Atlantic City: The Implications for Zoning Policy. *Journal of urban health : bulletin of the New York Academy of Medicine*, 91(1), pp.62–71.
- Jestico, B., Nelson, T. & Winters, M., 2016. Mapping ridership using crowdsourced

- cycling data. *Journal of Transport Geography*, 52, pp.90–97.
- Johnson, S.D., 2004. The Stability of Space-Time Clusters of Burglary. *British Journal of Criminology*, 44(1), pp.55–65.
- Kendall, P., 2008. *Public Health Approach to Alcohol Policy*, Office of the Provincial Health Officer: Victoria. Available at:
<http://www.health.gov.bc.ca/library/publications/year/2008/alcoholpolicyreview.pdf>.
- Kent, J., Leitner, M. & Curtis, A., 2006. Evaluating the usefulness of functional distance measures when calibrating journey-to-crime distance decay functions. *Computers, Environment and Urban Systems*, 30(2), pp.181–200.
- Kim, Y.A., 2016. Examining the Relationship Between the Structural Characteristics of Place and Crime by Imputing Census Block Data in Street Segments: Is the Pain Worth the Gain? *Journal of Quantitative Criminology*, pp.1–44.
- Kraus, L. et al., 2009. Association of average daily alcohol consumption, binge drinking and alcohol-related social problems: results from the German Epidemiological Surveys of Substance Abuse. *Alcohol and alcoholism (Oxford, Oxfordshire)*, 44(3), pp.314–20.
- Kulldorff, M., 2001. Prospective time periodic geographical disease surveillance using a scan statistic. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 164(1), pp.61–72.
- Kypri, K. et al., 2008. Alcohol outlet density and university student drinking : a national study. *Addiction*, 103, pp.1131–1138.
- Kypri, K. et al., 2011. Effects of restricting pub closing times on night-time assaults in an Australian city. *Addiction (Abingdon, England)*, 106(2), pp.303–10.
- Kypri, K., McElduff, P. & Miller, P., 2014. Restrictions in pub closing times and lockouts in Newcastle, Australia five years on. *Drug and Alcohol Review*, 33(3), pp.323–326.
- Lang, E. et al., 1998. Can training bar staff in responsible serving practices reduce alcohol-related harm? *Drug and alcohol review*, 17(1), pp.39–50.
- Leary, M.O. & O’Leary, M., 2011. Modeling Criminal Distance Decay. *Cityscape*, 13(3), pp.161–198.
- Levine, N. et al., 2000. CrimeStat: A Spatial Statistics Program for the Analysis of Crime

- Incident Locations. In *National Criminal Justice Reference Service*. Washington, DC: Ned Levine & Associates.
- Liang, W. & Chikritzhs, T., 2011. Revealing the link between licensed outlets and violence: counting venues versus measuring alcohol availability. *Drug and alcohol review*, 30(5), pp.524–35.
- Lightowlers, C., Mark, E. & Trammers, M., 2013. *Assessing the Effects of Heavy Episodic Drinking on Interpersonal Assault Using Multilevel Modelling*,
- Lipton, R. & Gruenewald, P., 2002. The spatial dynamics of violence and alcohol outlets. *Journal of studies on alcohol*, 63(2), pp.187–95.
- Livingston, M., 2011. A longitudinal analysis of alcohol outlet density and domestic violence. *Addiction (Abingdon, England)*, 106(5), pp.919–25.
- Livingston, M., 2008. Alcohol outlet density and assault: a spatial analysis. *Addiction (Abingdon, England)*, 103(4), pp.619–28.
- Livingston, M., 2011. Alcohol outlet density and harm: comparing the impacts on violence and chronic harms. *Drug and alcohol review*, 30(5), pp.515–23.
- Livingston, M., 2010. The ecology of domestic violence: the role of alcohol outlet density. *Geospatial health*, 5(1), pp.139–49.
- Livingston, M., Chikritzhs, T. & Room, R., 2007. Changing the density of alcohol outlets to reduce alcohol-related problems. *Drug and alcohol review*, 26(5), pp.557–66.
- Lynch, H.J. & Moorcroft, P.R., 2008. A spatiotemporal Ripley's K -function to analyze interactions between spruce budworm and fire in British Columbia, Canada. *Canadian Journal of Forest Research*, 38(12), pp.3112–3119.
- Macdonald, S. et al., 2005. The criteria for causation of alcohol in violent injuries based on emergency room data from six countries. *Addictive behaviors*, 30(1), pp.103–13.
- Mair, C. et al., 2013. Varying impacts of alcohol outlet densities on violent assaults: explaining differences across neighborhoods. *Journal of studies on alcohol and drugs*, 74(1), pp.50–8.
- Malleson, N. & Andresen, M.A., 2014. The impact of using social media data in crime rate calculations: shifting hot spots and changing spatial patterns. *Cartography and Geographic Information Science*, 42(2), pp.1–10.
- Markowitz, S., 2005. Alcohol, Drugs and Violent Crime. *International Review of Law*

- and Economics*, 25(1), pp.20–44.
- Markowitz, S. et al., 2012. Estimating the Relationship between Alcohol Policies and Criminal Violence and Victimization. *German Economic Review*, 13(4), pp.416–435.
- Markowitz, S., 2000. The Price of Alcohol , Wife Abuse , and Husband Abuse. *Southern Economic Journal*, 67(2), pp.279–303.
- Markowitz, S. & Grossman, M., 2000. The effects of beer taxes on physical child abuse. *Journal of health economics*, 19(2), pp.271–82.
- Martínez, L.M. & Viegas, J.M., 2013. A new approach to modelling distance-decay functions for accessibility assessment in transport studies. *Journal of Transport Geography*, 26, pp.87–96.
- Matthews, K., Shepherd, J. & Sivarajasingham, V., 2006. Violence-related injury and the price of beer in England and Wales. *Applied Economics*, 38(6), pp.661–670.
- Matthews, S., 2009. *To compare regulatory and planning models which reduce crime in the night time economy*, The Winston Churchill Memorial Trust of Australia.
- Mazerolle, L. et al., 2012. Violence in and around Entertainment Districts: A Longitudinal Analysis of the Impact of Late-Night Lockout Legislation. *Law & Policy*, 34(1), pp.55–79.
- McFadden, A.J., Young, M. & Markham, F., 2015. Venue-Level Predictors of Alcohol-Related Violence: An Exploratory Study in Melbourne, Australia. *International Journal of Mental Health and Addiction*, 13(4), pp.506–519.
- McKinney, C.M. et al., 2009. Alcohol availability and intimate partner violence among US couples. *Alcoholism, clinical and experimental research*, 33(1), pp.169–76.
- McMillan, G.P., Hanson, T.E. & Lapham, S.C., 2007. Geographic variability in alcohol-related crashes in response to legalized Sunday packaged alcohol sales in New Mexico. *Accident; analysis and prevention*, 39(2), pp.252–7.
- Menéndez, P., Tusell, F. & Weatherburn, D., 2015. The effects of liquor licensing restriction on alcohol-related violence in NSW, 2008-13. *Addiction*, 110(10), pp.1574–1582.
- Millar, A.B. & Gruenewald, P.J., 1997. Use of spatial models for community program evaluation of changes in alcohol outlet distribution. *Addiction*, 92(January),

- pp.273–284.
- Miller, P. et al., 2012. The long-term effect of lockouts on alcohol-related emergency department attendances within Ballarat, Australia. *Drug and alcohol review*, 31(4), pp.370–6.
- Morrison, C. et al., 2015. Relating off-premises alcohol outlet density to intentional and unintentional injuries. *Addiction*, Available at: <http://doi.wiley.com/10.1111/add.13098>.
- Morrison, K.T. et al., 2012. International Journal of Geographical Application of Bayesian spatial smoothing models to assess agricultural self-sufficiency. *International Journal of Geographical Information Science*, 26(7), pp.37–41.
- Mumola, B.C.J., 1999. Bureau of Justice Statistics Special Report Substance Abuse and Treatment , State and Federal Prisoners , 1997. *Bureau of Justice Statistics*, 172871(January).
- Myrstol, B.A., 2012. The alcohol-related workload of patrol officers. *Policing: An International Journal of Police Strategies & Management*, 35(1), pp.55–75.
- Nakaya, T. & Yano, K., 2010. Visualising Crime Clusters in a Space-time Cube: An Exploratory Data-analysis Approach Using Space-time Kernel Density Estimation and Scan Statistics. *Transactions in GIS*, 14(3), pp.223–239.
- National Institute on Alcohol Abuse and Alcoholism, Drinking Levels Defined. Available at: <http://www.niaaa.nih.gov/alcohol-health/overview-alcohol-consumption/moderate-binge-drinking>.
- Nelson, T.A. et al., 2015. BikeMaps.org: A Global Tool for Collision and Near Miss Mapping. *Frontiers in Public Health*, 3(March), pp.1–8.
- Newton, A. & Hirschfield, A., 2009. Measuring violence in and around licensed premises: The need for a better evidence base. *Crime Prevention and Community Safety*, 11, pp.171–188.
- Nicholas, S., Kershaw, C. & Walker, A., 2007. *Crime in England and Wales 2006/07*, London. Available at: <https://www.ncjrs.gov/App/Publications/abstract.aspx?ID=242202>.
- Nielsen, A.L. et al., 2005. Alcohol, Ethnicity, and Violence: The Role of Alcohol Availability for Latino and Black Aggravated Assaults and Robberies. *The*

- Sociological Quarterly*, 46(3), pp.479–502.
- Nielsen, A.L. & Martinez, R., 2006. Reassessing the alcohol-violence linkage : Results from a multiethnic city. *Justice Quarterly*, 20(3), pp.37–41.
- Nielsen, A.L., Martinez, R. & Lee, M.T., 2005. Alcohol, Ethnicity, and Violence: The Role of Alcohol Availability for Latino and Black Aggravated Assaults and Robberies. *The Sociological Quarterly*, 46(3), pp.479–502.
- Norström, T., 2000. Outlet density and criminal violence in Norway, 1960-1995. *Journal of studies on alcohol*, 61(6), pp.907–11.
- Norström, T. & Ramstedt, M., 2005. Mortality and population drinking: a review of the literature. *Drug and alcohol review*, 24(6), pp.537–47.
- Norström, T. & Skog, O., 2005. Saturday opening of alcohol retail shops in Sweden: an experiment in two phases. *Addiction (Abingdon, England)*, 100(6), pp.767–76.
- Norström, T. & Skog, O., 2003. Saturday opening of alcohol retail shops in Sweden: an impact analysis. *Journal of studies on alcohol*, 64(3), pp.393–401.
- O’Sullivan, D. & Unwin, D.J., 2010. *Geographic Information Analysis* 2nd ed., John Wiley & Sons.
- O’Sullivan, D. & Unwin, D.J., 2003. *Geographic Information Analysis*, New Jersey: John Wiley and Sons.
- Parker, R.N. et al., 2011. Alcohol availability and youth homicide in the 91 largest US cities, 1984-2006. *Drug and alcohol review*, 30(5), pp.505–14.
- Pernanen, K. et al., 2002. *Proportions of Crimes Associated with Alcohol and Other Drugs in Canada*, Canadian Centre on Substance Abuse.
- Petrescu, S., 2016. Victoria church builds wall to keep out drug users, homeless campers. *Times Colonist*. Available at: <http://www.timescolonist.com/news/local/victoria-church-builds-wall-to-keep-out-drug-users-homeless-campers-1.5216914>.
- Piantadosi, S., Byar, D. & Green, S., 1988. The ecological fallacy. *American Journal of Epidemiology*, 127(5), pp.893–903.
- Plant, M. et al., 2000. Life Stage, Alcohol Consumption Patterns, Alcohol-Related Consequences, and Gender. *Substance abuse : official publication of the Association for Medical Education and Research in Substance Abuse*, 21(4), pp.265–281.
- Popova, S. et al., 2009. Hours and days of sale and density of alcohol outlets: impacts on

- alcohol consumption and damage: a systematic review. *Alcohol and alcoholism (Oxford, Oxfordshire)*, 44(5), pp.500–16.
- Port Moody Police Department, 2016. Bar Watch. Available at:
<http://portmoodypolice.ca/services-and-programs/bar-watch/>.
- Prasad, A., Iverson, L. & Liaw, A., 2006. Newer Classification and Regression Tree Techniques: Bagging and Random Forests for Ecological Prediction. *Ecosystems*, 9(2), pp.181–199.
- Pridemore, W.A. & Grubestic, T.H., 2012a. A spatial analysis of the moderating effects of land use on the association between alcohol outlet density and violence in urban areas. *Drug and alcohol review*, 31(4), pp.385–93.
- Pridemore, W.A. & Grubestic, T.H., 2012b. Community organization moderates the effect of alcohol outlet density on violence. *The British journal of sociology*, 63(4), pp.680–703.
- Pridemore, W. a. & Grubestic, T.H., 2011. Alcohol Outlets and Community Levels of Interpersonal Violence: Spatial Density, Outlet Type, and Seriousness of Assault. *Journal of Research in Crime and Delinquency*, 50(1), pp.132–159.
- Quigley, B., Leonard, K. & Collins, R., 2003. Characteristics of Violent Bars and Bar Patrons. *Journal of Studies on Alcohol*, 64(6), pp.765–772.
- Ratcliffe, J.H. et al., 2011. The Philadelphia Foot Patrol Experiment: a Randomized Controlled Trial of Police Patrol Effectiveness in Violent Crime Hotspots. *Criminology*, 49(3), pp.795–831.
- Ratcliffe, J.H., 2012. The Spatial Extent of Criminogenic Places: A Changepoint Regression of Violence around Bars. *Geographical Analysis*, 44(4), pp.302–320.
- Ratcliffe, J.H. & Rengert, G.F., 2008. Near-Repeat Patterns in Philadelphia Shootings. *Security Journal*, 21(1–2), pp.58–76.
- Rehm, J. et al., 2010. The relation between different dimensions of alcohol consumption and burden of disease: an overview. *Addiction (Abingdon, England)*, 105(5), pp.817–43.
- Reid, R.J., Hughey, J. & Peterson, A.N., 2003. Generalizing the Alcohol Outlet–Assaultive Violence Link: Evidence from a U.S. Midwestern City. *Substance Use & Misuse*, 38(14), pp.1971–1982.

- Resko, S.A. et al., 2010. Alcohol availability and violence among inner-city adolescents: A multi-level analysis of the role of alcohol outlet density. *American journal of community psychology*, 46(3–4), pp.253–62.
- Robertson, C. et al., 2010. Review of methods for space-time disease surveillance. *Spatial and spatio-temporal epidemiology*, 1(2–3), pp.105–16.
- Robertson, C., McLeman, R. & Lawrence, H., 2015. Winters too warm to skate? Citizen-science reported variability in availability of outdoor skating in Canada. *Canadian Geographer*, 59(4), pp.383–390.
- Room, R. et al., 2012. Times to drink: cross-cultural variations in drinking in the rhythm of the week. *International journal of public health*, 57(1), pp.107–17.
- Rossow, I. & Norström, T., 2012. The impact of small changes in bar closing hours on violence. The Norwegian experience from 18 cities. *Addiction (Abingdon, England)*, 107(3), pp.530–7.
- Rossow, I. & Norström, T., 2012. The impact of small changes in bar closing hours on violence. The Norwegian experience from 18 cities. *Addiction (Abingdon, England)*, 107(3), pp.530–7.
- Sampson, R.J., 1997. Neighborhoods and Violent Crime: A Multilevel Study of Collective Efficacy. *Science*, 277(5328), pp.918–924.
- Sampson, R.J. & Groves, W.B., 1989. Community Structure and crime: Testing social-disorganization theory. *American Journal of Sociology*, 94(4), pp.774–802.
- Sánchez, A.I. et al., 2011. Policies for alcohol restriction and their association with interpersonal violence: a time-series analysis of homicides in Cali, Colombia. *International journal of epidemiology*, 40(4), pp.1037–46.
- Scanfeld, D., Scanfeld, V. & Larson, E.L., 2010. Dissemination of health information through social networks: twitter and antibiotics. *American journal of infection control*, 38(3), pp.182–8.
- Schofield, T.P. & Denson, T.F., 2013. Alcohol Outlet Business Hours and Violent Crime in New York State. *Alcohol and alcoholism (Oxford, Oxfordshire)*, 48(3), pp.1–7.
- Scribner, R. et al., 1999. Alcohol Availability and Homicide in New Orleans : Conceptual Considerations for Small Area Analysis of the Effect of Alcohol Outlet Density. *Jornal of Studies on Alcohol*, 60, pp.310–316.

- Scribner, R.A. et al., 2010. An Ecological Analysis of Alcohol-Outlet Density and Campus-Reported Violence at 32 US Colleges. *Journal of Studies on Alcohol and Drugs*, (March), pp.184–191.
- Scribner, R.A., MacKinnon, D.P. & Dwyer, J.H., 1995. The risk of assaultive violence and alcohol availability in Los Angeles County. *American journal of public health*, 85(3), pp.335–40.
- Seaman, D.E. et al., 1999. Effects of sample size on kernel home range estimates. *The Journal of Wildlife Management*, 63(2), pp.739–747.
- Sherman, L., Buerger, M. & Gartin, P., 1989. *Beyond dial-a-cop: A randomized test of Repeat Call Policing (RECAP)*, Washington, DC.
- Sivarajasingam, V., Matthews, K. & Shepherd, J., 2006. Price of beer and violence-related injury in England and Wales. *Injury*, 37(5), pp.388–94.
- Snowden, A.J. & Pridemore, W.A., 2013a. Alcohol and Violence in a Nonmetropolitan College Town: Alcohol Outlet Density, Outlet Type, and Assault. *Journal of Drug Issues*, 43(3), pp.357–373.
- Snowden, A.J. & Pridemore, W.A., 2013b. Alcohol Outlets, Social Disorganization, Land Use, and Violence in a Large College Town: Direct and Moderating Effects. *Criminal Justice Review*, 38(1), pp.29–49.
- Son, C.H. & Topyan, K., 2011. The effect of alcoholic beverage excise tax on alcohol-attributable injury mortalities. *The European journal of health economics : HEPAC : health economics in prevention and care*, 12(2), pp.103–13.
- Speer, P. et al., 1998. Violent Crime and Alcohol Availability: Relationships in an Urban Community. *Journal of Public Health Policy*, 19(3), pp.303–318.
- Spicer, V. et al., 2012. Bars on blocks: A cellular automata model of crime and liquor licensed establishment density. *Computers, Environment and Urban Systems*, 36(5), pp.412–422.
- Sridharan, S., Vujic, S. & Koopma, S.J., 2003. *Intervention Time Series Analysis of Crime Rates*, Rockville, MD, USA.
- Statistics Canada, 2009. Dissemination Area. Available at:
<http://www12.statcan.ca/census-recensement/2006/ref/dict/geo021-eng.cfm>.
- Stevenson, R.J., Lind, B. & Weatherburn, D., 1999. The relationship between alcohol

- sales and assault in New South Wales, Australia. *Addiction (Abingdon, England)*, 94(3), pp.397–410.
- Stockwell, T. et al., 2002. Alcohol consumption, setting, gender and activity as predictors of injury: a population-based case-control study. *Journal of studies on alcohol*, 63(3), pp.372–9.
- Stockwell, T. et al., 2009. Changes in per capita alcohol sales during the partial privatization of British Columbia's retail alcohol monopoly 2003-2008: a multi-level local area analysis. *Addiction (Abingdon, England)*, 104(11), pp.1827–36.
- Stockwell, T., Auld, M.C., et al., 2012. Does minimum pricing reduce alcohol consumption? The experience of a Canadian province. *Addiction (Abingdon, England)*, 107(5), pp.912–20.
- Stockwell, T. et al., 2011. Impact on alcohol-related mortality of a rapid rise in the density of private liquor outlets in British Columbia: a local area multi-level analysis. *Addiction (Abingdon, England)*, 106(4), pp.768–76.
- Stockwell, T. et al., 2015. Relationships Between Minimum Alcohol Pricing and Crime During the Partial Privatization of a Canadian Government Alcohol Monopoly. *Journal of Studies on Alcohol and Drugs*, (July), pp.628–634.
- Stockwell, T., Zhao, J., et al., 2012. The raising of minimum alcohol prices in Saskatchewan, Canada: impacts on consumption and implications for public health. *American journal of public health*, 102(12), pp.e103-10.
- Stockwell, T. & Chikritzhs, T., 2009. Do relaxed trading hours for bars and clubs mean more relaxed drinking? A review of international research on the impacts of changes to permitted hours of drinking. *Crime Prevention and Community Safety: An International Journal*, 11(3), pp.153–170.
- Stockwell, T., Lang, E. & Rydon, P., 1993. High risk drinking settings: the association of serving and promotional practices with harmful drinking. *Addiction (Abingdon, England)*, 88(11), pp.1519–26.
- Stucky, T.D. & Ottensmann, J.R., 2009. Land use and violent crime. *Criminology*, 47(4), pp.1223–1264.
- Sviridoff, M. et al., 1992. *The neighborhood effects of street-level drug enforcement: Tactical narcotics teams in New York*, New York, NY.

- Taylor, B., Koper, C.S. & Woods, D.J., 2011. A randomized controlled trial of different policing strategies at hot spots of violent crime. *Journal of Experimental Criminology*, 7(2), pp.149–181.
- Toomey, T.L. et al., 2012. Is the density of alcohol establishments related to nonviolent crime? *Journal of studies on alcohol and drugs*, 73(1), pp.21–5.
- Toomey, T.L. et al., 2012. The Association Between Density of Alcohol Establishments and Violent Crime Within Urban Neighborhoods. *Alcoholism: Clinical and Experimental Research*, 36(8), pp.1468–1473.
- Treno, A.J. et al., 2007. The impact of outlet densities on alcohol-related crashes: a spatial panel approach. *Accident; analysis and prevention*, 39(5), pp.894–901.
- Treno, A.J., Grube, J.W. & Martin, S.E., 2003. Alcohol availability as a predictor of youth drinking and driving: a hierarchical analysis of survey and archival data. *Alcoholism, clinical and experimental research*, 27(5), pp.835–40.
- Vancouver Island Health Authority, 2014. Harm Reduction Services, South Vancouver Island Distribution Sites and Collection Statistics. Available at: http://www.viha.ca/NR/rdonlyres/A5875CEF-2150-4934-987D-AD8B6EC3B58D/0/fs_needle_collection_status_Jan2014update.pdf.
- Veall, M.R. & Zimmermann, K.F., 1996. Pseudo R Squared Measures for some Common Limited Dependent Variable Models. *Journal of Economic Surveys*, 10(3), pp.241–259.
- Vingilis, E. et al., 2008. A tale of two cities: the effect of extended drinking hours in licensed establishments on impaired driving and assault charges. *Traffic injury prevention*, 9(6), pp.527–33.
- Vingilis, E. et al., 2008. Impact of extended drinking hours in Ontario on motor-vehicle collision and non-motor-vehicle collision injuries. *J Stud Alcohol Drugs*, 68(6), pp.905–911.
- Vingilis, E. et al., 2005. Road safety impact of extended drinking hours in Ontario. *Accident; analysis and prevention*, 37(3), pp.549–56.
- Vingilis, E. et al., 2006. The impact of Ontario's extended drinking hours on cross-border cities of Windsor and Detroit. *Accident; analysis and prevention*, 38(1), pp.63–70.
- Wagenaar, A.C., Tobler, A.L. & Komro, K.A., 2010. Effects of alcohol tax and price

- policies on morbidity and mortality: a systematic review. *American journal of public health*, 100(11), pp.2270–8.
- Walker, B.B., Schuurman, N. & Columbia, B., 2012. Environmental Correlates with Violent Injury the Burden of Injury Physical Environment. *GEOMATICA*, 66(4), pp.269–278.
- Waller, M.W. et al., 2012. Relationships among alcohol outlet density, alcohol use, and intimate partner violence victimization among young women in the United States. *Journal of interpersonal violence*, 27(10), pp.2062–86.
- Waller, M.W. & Iritani, B.J., 2012. Violence Victimization of Young Men in Heterosexual Relationships: Does Alcohol Outlet Density Influence Outcomes? *Violence Vict.*, 27(4), pp.527–547.
- Watt, K. et al., 2004. Risk of injury from acute alcohol consumption and the influence of confounders. *Addiction (Abingdon, England)*, 99(10), pp.1262–73.
- Wechsler, H. et al., 2002. Secondhand effects of student alcohol use reported by neighbors of colleges: the role of alcohol outlets. *Social science & medicine (1982)*, 55(3), pp.425–35.
- Weisburd, D., 2015. The law of crime concentration and the criminology of place. *Criminology*, 53(2), pp.133–157.
- Wells, S. & Graham, K., 2003. Aggression involving alcohol: relationship to drinking patterns and social context. *Addiction (Abingdon, England)*, 98(1), pp.33–42.
- Wheeler, D.C. & Waller, L.A., 2008. Comparing spatially varying coefficient models: a case study examining violent crime rates and their relationships to alcohol outlets and illegal drug arrests. *Journal of Geographical Systems*, 11(1), pp.1–22.
- White, G.F., Gainey, R.R. & Triplett, R. a., 2015. Alcohol Outlets and Neighborhood Crime: A Longitudinal Analysis. *Crime & Delinquency*, 61(1).
- Wilkinson, C. & Livingston, M., 2012. Distances to on- and off-premise alcohol outlets and experiences of alcohol-related amenity problems. *Drug and alcohol review*, 31(4), pp.394–401.
- World Health Organization, 2011. *Global status report on alcohol and health*, Geneva. Available at:
http://www.who.int/substance_abuse/publications/global_alcohol_report/msbgsrupr

ofiles.pdf.

- Xie, Z. & Yan, J., 2008. Kernel Density Estimation of traffic accidents in a network space. *Computers, Environment and Urban Systems*, 32(5), pp.396–406.
- Yu, Q. et al., 2010. Multilevel spatio-temporal dual changepoint models for relating alcohol outlet destruction and changes in neighbourhood rates of assaultive violence. *GeoSpatial Health*, 2(2), pp.161–172.
- Yu, Q., Li, B. & Scribner, R.A., 2009. Hierarchical additive modeling of nonlinear association with spatial correlations — An application to relate alcohol outlet density and neighborhood assault rates. *Statistics in Medicine*, 28, pp.1896–1912.
- Zhang, X. et al., 2015. Changes in density of on-premises alcohol outlets and impact on violent crime, Atlanta, Georgia, 1997-2007. *Prev Chronic Dis*, 12(8), p.E84.
- Zhao, J. et al., 2013. The relationship between minimum alcohol prices, outlet densities and alcohol-attributable deaths in British Columbia, 2002-09. *Addiction (Abingdon, England)*, 108(6), pp.1059–69.
- Zhu, L., Gorman, D.M. & Horel, S., 2004. Alcohol outlet density and violence: a geospatial analysis. *Alcohol and Alcoholism*, 39(4), pp.369–75.
- Zimmer, M. & Proferes, N.J., 2014. A topology of Twitter research: disciplines, methods, and ethics. *Aslib Journal of Information Management*, 66(3), pp.250–261.