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Suicide by firearm, suicide fatality, and firearm availability

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SUICIDE BY FIREARM, SUICIDE FATALITY, AND FIREARM AVAILABILITY

by

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ABSTRACT

An Analysis of the Relationship between Gun Availability and Suicide in the City of Chicago, 1990-1997

by

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This study has three objectives. The first two objectives are to determine if neighborhood level gun availability has an effect on suicide method and suicide fatality. The third is to test that para-suicides (i.e., attempted suicides) with a mental disorder are more likely than para-suicides without a mental disorder to attempt suicide by firearm. Neighborhood is defined by zip code. The number of homicides for each zip code divided by the number of firearm related homicides in each zip code is used as a proxy for neighborhood level gun availability. Data on suicides and para-suicides occurring in Chicago from 1990-1997 are combined. Generalized linear mixed models are used to explore the first two objectives. A chi-square test is used for the third. We conclude that neighborhood level gun availability increases the likelihood of choosing a firearm as the suicide method and has no effect on the likelihood of a suicide being fatal. Para-suicides with a mental disorder are less likely to attempt suicide by firearm.

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CHAPTER 1

INTRODUCTION

Firearms have become the most common method used to commit suicide in the United States and are responsible for thousands of homicides each year (Streib et al., 2007; Weiner et al., 2007). They are also linked to other disturbing outcomes, such as violence and injuries (Baroni et al., 2006; Weiner et al., 2007). Current research shows that owning a firearm in the home increases the risk of committing suicide by firearm for all genders and ages (Wiebe, 2003), and in places where firearm ownership level is higher, the suicide rate is higher (Miller et al., 2002). However, there is little research on how neighborhood level gun availability relates to both the likelihood of a suicide being fatal and the likelihood of choosing a firearm as the method of suicide.

Differences in Suicide by Age, Gender, and Ethnicity

In 2004, 31,647 people committed suicide in the United States, a rate of 10.8 per 100,000 population (Miniño et al., 2006). Suicide was the nation's eleventh leading cause of death in 2004 and the third leading cause of death for persons 15-24 years of age (Miniño et al., 2006). Among all suicides in 2004, 52% (16,603) were committed with a firearm, making it the leading method of suicide (Miniño et al., 2006).

Methods of suicide differ among males and females. Males tend to use a firearm where females use drug poisoning as their first method of choice with firearms as the second (Kposowa et al., 2006). Current research has shown that females have higher para-suicide (i.e., attempted suicide) rates than males, but males have higher completed suicide rates than females (Kposowa et al., 2006; Beautrais, 2006). Males are four times more likely than females to die from suicide (CDC, 2007). Research has provided many explanations for this. One reason is that even with equal intent to die males tend to choose more lethal methods to commit suicide than females (Beautrais, 2006). Some research indicates that females, more than males, are concerned with appearance, and therefore, use firearms less in committing suicide (Kposowa et al., 2006). Another reason is that if females do use a firearm they are less apt to shoot themselves in the face for fear of disfigurement which could result in a failed suicide (Kposowa et al., 2006). Furthermore, females may be more prone to attempt suicide due to a gender-related vulnerability to mental disorders and psychosocial stresses like motherhood, marriage, childhood sexual abuse, domestic, depression, and violence, but they may not actually complete the act because they are more willing to ask for help and more likely to be offered help (Beautrais, 2006).

Data also shows the rate of suicide varies according to age. Suicide rates increase with age and are higher among people 65 years and older (CDC, 2007). The rate of suicide by firearm in 2004 increased with age, beginning at 5.46 per 100,000 among 15-24 year olds, increasing to 8.05 per 100,000 among 45-54 year olds, and reaching 10.34 per 100,000 for persons 65-85+ years old (CDC, 2004). Almost two thirds of all suicides by firearm, however, were among persons under 55 years of age (CDC, 2004).

Just as current research has shown that suicide rates and methods differ among gender and age groups, there are also differences among individuals of different races. Most of the current research concentrates on blacks and whites. During the years 1980-1995 the rate of suicide for black males increased 146% (Ialongo et al., 2002; Joe et al., 2007). Within the same time period, the rate of suicide by firearm for black males increased 133% for ages 15-19 and 24% for ages 20-24 (Ialongo et al., 2002; Joe et al., 2007). In comparison, the rate of suicide by firearm for whites increased by only 7% among ages 15-19, and the rate of suicide by firearm among whites ages 20-24 did not increase at all (Ialongo et al., 2002; Joe et al., 2007). Even though there was an increase in suicide rates for blacks, whites continue to commit suicide at a higher rate. In 2004 whites committed suicide by firearm (7.26 per 100,000) at a little less than three times the rate of blacks (2.69 per 100,000) and hispanics (2.15 per 100,000) (CDC, 2004). Blacks most at risk for suicide are much younger than whites and have a smaller age window of vulnerability (Garlow et al., 2005; Joe et al., 2007). Black males are twice as likely as white males to choose suicide by firearm (Joe et al., 2007). Black females have lower suicide rates than other females in the United States (Marion et al., 2003). Black females also have a narrow age window of vulnerability with the majority of suicides occurring between ages 20-45 and very few episodes occurring before or after this age group (Garlow et al., 2005).

Purpose of Study

This study has the following three objectives:

1. Explore the relationship that various individual level and neighborhood level predictors have on the likelihood of choosing firearm as the method of suicide. In particular, determine if neighborhood level gun availability has a significant effect on the likelihood of choosing firearm as the suicide method.
2. Explore the relationship that various individual level and neighborhood level predictors have on the likelihood of a suicide being fatal. More importantly, determine if neighborhood level gun availability has a significant effect on the likelihood of a suicide being fatal.
3. Determine if para-suicides (i.e., attempted suicides) with a mental disorder are more likely than para-suicides without a mental disorder to use a firearm to attempt suicide.

The data set used in this study contains both individual and neighborhood level data for each case. This is considered multi-level data. Examples of individual level data are variables such as age, gender, mortality, method of suicide and zip code of the individual's residence. In this study neighborhood is defined by one's zip code. Neighborhood level data examples are percent of white residents, percent of black residents, percent of residents who own a home and percent of residents below the poverty line. These data are further explored later in the chapter. For analysis of this multi-level data, random effects are added into the model. There is a random effect for the neighborhood and random effects on the individual level variables such as age, gender, suicide method and mortality associated with each neighborhood. A generalized linear mixed model (GLMM) contains both fixed effects and random effects. Thus GLMM's are used to explore the relationships expressed in objectives 1 and 2. To obtain the parameter estimates for each GLMM, a Bayesian approach using MCMC, specifically Gibbs sampling, is taken. These methods are further explained in Chapter 4.

Thesis Structure

The remainder of this chapter explains the data sets and the meaning of neighborhood level gun availability. Chapter 2 contains an exploratory analysis of the data. Chapter 3 describes the process of obtaining the initial model selections for the GLMM's. Chapter 4 reviews the methodology of MCMC, specifically Gibbs sampling, and provides an overview of model specification, convergence diagnostics and model results. Chapter 5 contains the sub-analysis of para-suicides. In particular, it contains the method used to evaluate objective 3 and the results. A discussion of the study is found in Chapter 6 along with study limitations and future work.

The Data

Three data sets are used in this study. Morgue admissions spanning the years 1990-1997 are obtained from the Chicago Department of Public Health. Data on hospital admissions are obtained from Illinois Hospital Containment Center for the years 1990-1997. Data are collected from the 1990 Census from the United States Census Bureau. Each set is detailed below.

Morgue Data

Data on completed suicides and homicides are compiled from annual mortality data files of the Chicago Department of Public Health. Data from the morgue available for each individual include type of death (homicide or suicide), method of death (gun or other), age, gender and zip code.

The morgue data set consists of 10,062 cases where 2,284 are individuals who committed suicide. Among these individuals who committed suicide, 79% are male. The average age for males who committed suicide is 42 years and for females who committed suicide is 44 years. Forty two percent of the cases are suicide by firearm with 88% being male. The use for the homicide data is further explained later in this chapter in the section about measuring neighborhood level gun availability.

Hospital Data

Hospital admission records involving either a suicide or para-suicide and spanning the years 1990-1997 are obtained from the Illinois Hospital Containment Center. Theses files contain information from acute care facilities that were operating in Chicago between 1990-1997, but they do not include data from Veteran's Administration hospitals, nor from psychiatric hospitals. Variables available for each individual are gender, age, zip code, mortality, method of suicide or para-suicide (gun or other) and mental status.

There are 10,521 suicide/para-suicide hospital admissions in the Chicago area for the years 1990-1997. Admissions are mostly female at 64%. The average age for females and males is 29 and 32 years old, respectively. Approximately 81% of the suicide/para-suicide hospital admissions are individuals with a mental disorder. Mental disorders are identified by International Classification of Diseases mental disorder codes: 290 – 319 (WHO, 1998) and categorized into the following seven groups: psychosis, neurotic, adjustment reaction, depression, alcohol psychoses or dependence, drug psychoses or dependence, and other mental disorder. Table 1 contains the distribution of the mental disorders.

Table 1: Distribution of Mental Disorders

Mental Status	Number of Admissions	% of Total
Psychosis	805	9.43
Neurotic	254	2.98
Adjustment Reaction	1147	13.44
Depression	3615	42.35
Alcohol Psychoses/ Dependence	583	6.83
Drug Psychoses/ Dependence	1917	22.45
Other mental disorder	214	2.51

Census Data

In the morgue and hospital data described above certain individual level variables of interest, such as race and socioeconomic characteristics, are not available. However, the socioeconomic characteristics of a neighborhood area can be used as proxies for individual characteristics (Geronimus and Bound, 1998; Geronimus et al., 1996). In this project, neighborhood is defined by an individual's zip code. Socioeconomic measures are obtained for each neighborhood using the 1990 Census data from the United States Census Bureau.

The available census variables can be divided into 4 main domains which are racial layout, income, housing and social characteristics. Percent of residents who are white, black or hispanic belong to the racial layout domain. Percent of residents who are below the poverty line and percent of residents who are unemployed constitute the income division. Percent of residents who rent and percent of residents who own a home form the housing domain. Percent of single females with no children, percent of single females with children, and the percent of residents who speak another language besides English at home make up the social characteristics domain.

Suicide and Para-suicide Cases

In order to reduce the possibility of double counting a case, it is assumed that hospitalization cases that resulted in death also appear in the annual mortality files. Therefore, 32 hospitalization cases that resulted in death are excluded from the study. To reduce the possibility of potential misdiagnosis of suicide, any cases involving individuals five years old or younger are removed from the study. This results in removing one case from the study. Because this study is about neighborhood effects, 33 cases are removed in which no zip code is available. Any zip code that has a total population of 500 or less is removed from this study which results in the exclusion of 37 additional cases.

Data on completed suicides (morgue data) are combined with data on para-suicides (hospital data) making a total of 12,701 cases. Of the 12,701 cases, 18% are fatal and 7.5% are done by firearm. Suicides and para-suicides are identified by International Classification of Diseases external causes of injury codes: E950-E959 (WHO, 1998) and are classified into two categories according to suicide method. The total number of cases for each suicide method is obtained by calculating the sum of the number of suicides and the number of para-suicides for the given method. For example, the total number of firearms related cases (957) include 96% suicides (Table 2) and 4% para-suicides (not shown). Firearms are the most fatal at 96% in comparison to other suicide methods at only 11.3% being fatal.

Table 2: Distribution of Suicides and Para-suicides-Chicago, Illinois 1990-1997

	Complete sample	Male	Female	Minor Below 18	Adult 18 and over
	% of total*	% of total*	% of total*	% of total*	% of total*
Suicide Method	% fatal†	% fatal†	% fatal†	% fatal†	% fatal†
Firearms (957)	7.5	15.1	1.6	3.2	8.1
	96	96.1	95.6	93.8	96.1
Other□ (11,744)	92.5	84.9	98.4	96.8	91.9
	11.3	20.4	5.1	2.5	12.5
Total Episodes	12701	5587	7114	1502	11199
Total Fatal Episodes	2244	1779	465	81	2163

*Percentage of all episodes coded with the particular suicide method (for example, 7.5% of all episodes were with firearms). †Percentage of completed suicides from each suicide method (for example, 96.0% of episodes involving firearms were lethal). □Episodes involving all other methods, including episodes involving unknown methods and multiple methods (for example, firearms and poisons).

Neighborhood Level Gun Availability

In current research, various methods have been used to measure gun availability. These include using the percentage of suicides with a firearm (Hemenway et al., 2000), firearm production within the U.S. as a whole (McDowall 1986), legal handgun permits within a single city, survey-based estimates (Miller et al., 2007) and subscription rates to magazines aimed at gun users, such as *Guns and Ammo* (Shenassa et al., 2006). Another popular proxy is Cook's index which is calculated by averaging the percentage of all suicides committed with a firearm and the percentage of all homicides committed with a firearm for all age groups (Cook, 1979; Miller et al., 2001). Different versions of Cook's Index, such as eliminating certain age groups or to include accidental firearm deaths, have also been used (Shenassa et al., 2006). However, current research shows that the proportion of firearm related homicides alone is a useful predictor of gun availability across small areas such as neighborhoods (Shenassa et al., 2006). Therefore, for this study, neighborhood level gun availability is measured by the proportion of firearm related homicides for the given zip code.

Homicide cases are obtained from the morgue data described earlier. Firearm related homicides are classified using the International Classification of Diseases, 9th revision, (ICD-9) external causes of injury codes 965.0, 965.2, 965.3, and 965.4 (WHO, 1980). The number of homicides for each zip code is divided by the number of firearm related homicides in each zip code. This proportion is then used to represent neighborhood level gun availability.

CHAPTER 2

EXPLORATORY DATA ANALYSIS

This chapter further explores the data set for this study. The exploratory data analysis will aid in gaining further insight into the data and observing any trends.

Differences of Suicides and Para-suicides among Age and Gender

Similar to current literature, females are more likely to attempt suicide (93% versus 68%), but males are more likely to perish. For all suicide methods, males are 6.67 times more likely than females to commit suicide (95% CI 6.03 to 7.37). Adults are 4.19 times more likely than minors to perish (95% CI 5.58 to 3.39). Suicide by firearm is 190.15 times more fatal than using another method (95% CI 162.75 to 222.17).

Compared with hospital admissions that did not result in death, fatal episodes are more likely to involve males and older people (Figure 1). Among para-suicides, the median age for females and males is 27 and 31 years of age, respectively. For suicide cases, the median age for females and males is 41 and 38 years old, respectively. Of the para-suicides, more are likely to be female (OR 6.67, 95% CI 6.03 to 7.37) and younger than the individuals who committed suicide (Figure 1).

Males are 10.9 times more likely than females to choose suicide by firearm (95% CI 9.26 to 12.85). Of the males that choose suicide by firearm, 75% are under the age of 61.

Seventy five percent of males who do not choose suicide by firearm are 51 years of age or younger.

Figure 1: Box-and-whisker Plots of Para-suicides and Suicides by Age and Gender:

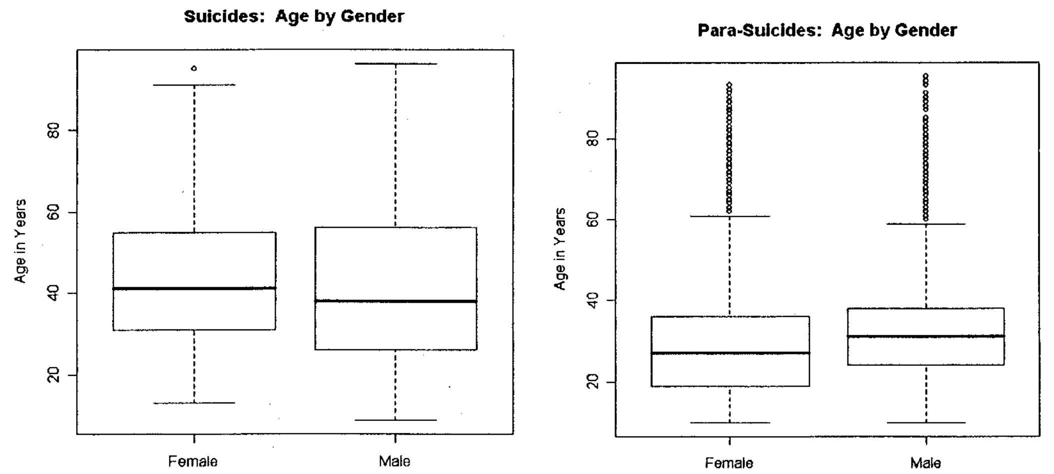
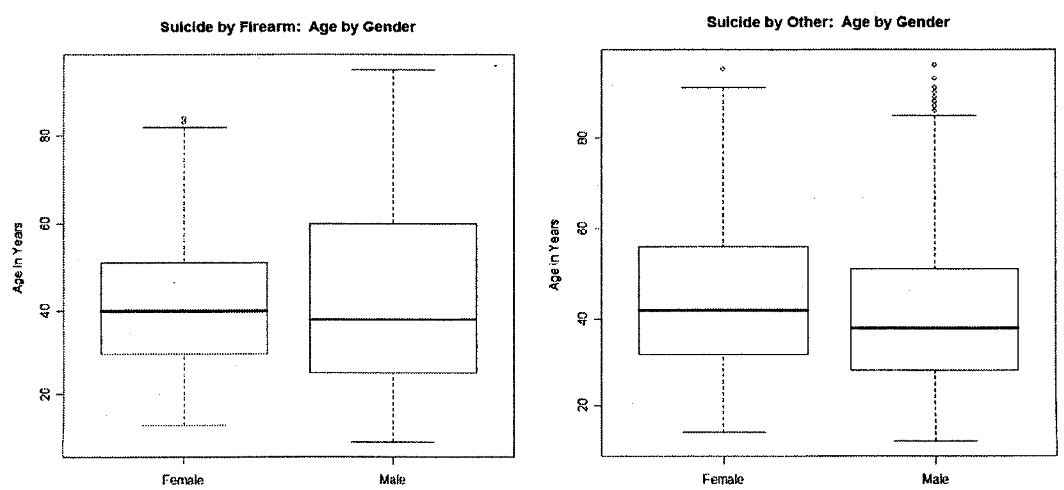


Figure 2: Box-and-whisker Plots of Suicide Method by Age and Gender:



Neighborhood Level Gun Availability, Suicide Fatality, and Suicide Method

The purpose of this study is to explore how neighborhood level gun availability relates to suicide fatality and choice of suicide method. Figure 3 is a scatterplot of the proportion of completed suicides versus neighborhood level gun availability for each zip code in the study. A linear regression is examined to detect a general trend or relationship between the two variables. In figure 3 there are two potential outliers. These are zip codes in which only morgue data are available, and there is no significant reason to remove these zip codes from the study. Figure 4 is also a scatterplot that plots the proportions of suicides and para-suicides by firearm against neighborhood level gun availability for each zip code with a linear regression. These plots indicate that the relationships may be non linear.

Figure 3: Neighborhood Level Gun Availability vs. Completed Suicides

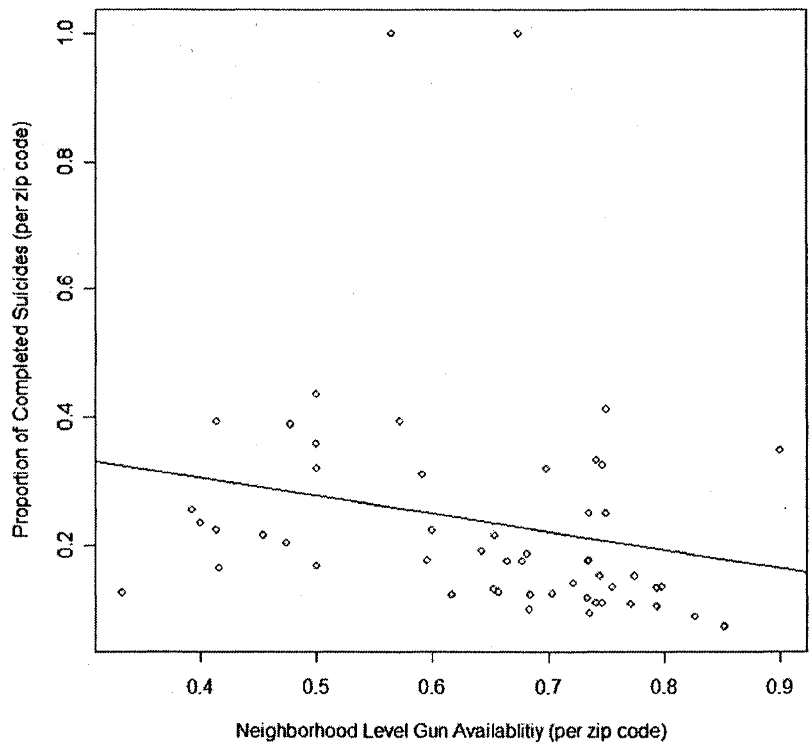
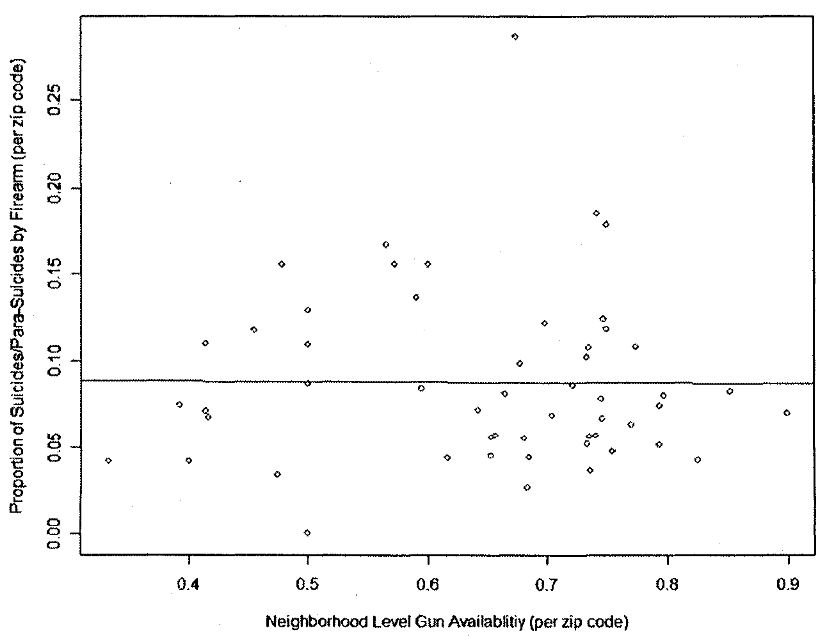


Figure 4: Neighborhood Level Gun Availability vs. Firearm Suicides/Para-Suicides



CHAPTER 3

INITIAL MODEL SELECTION

Explanatory variables for this study are individual variables such as age (AGE), mortality (MORTAL), suicide method (METHOD) and gender (GENDER) and neighborhood level variables such as gun availability (PGUN), percentage of unemployment (UNEMPL), poverty (POV), white residents (WHITE), black residents (BLACK), hispanic residents (HISP), homes where English is not the primary language (LANG), rent (RENT), own (OWN), single female residents with no children (FEM), and single female residents with children under 18 years of age (FEMCH). As explained in Chapter 1, GLMM's are used to explore objectives 1 and 2. Each GLMM will include the individual variables, age and gender, as well as neighborhood level gun availability. Model selection determines which of the remaining neighborhood level variables are most appropriate to use in the GLMM's. Because of the computational intensity of running the GLMM programs we do a preliminary model selection using general linear models. For aid in model selection a series of logistic regressions are run for each response and AIC values are compared. AIC is a model selection criteria that penalizes for adding predictors to a model (Kutner et al., 2004). It is a measure of goodness of fit of an estimated statistical model, where $\mathrm{AIC} = 2k - 2\ln(L)$, where k is the number of parameters and L is the likelihood function (Akaike, 2007). The smaller the value of the AIC, the better the model fits the data.

A common problem in studies such as these is collinearity among the variables. In model selection, one not only wants to find the most appropriate variables to use, but also variables that are not highly correlated. Collinear variables in the model violate the assumption of the GLMM's which is that the linear predictors are independent. The logistic regression models, the scatterplot matrix and the correlation matrix help in identifying any collinearity among the neighborhood level variables.

Scatter Plot Matrix and Correlation Matrix

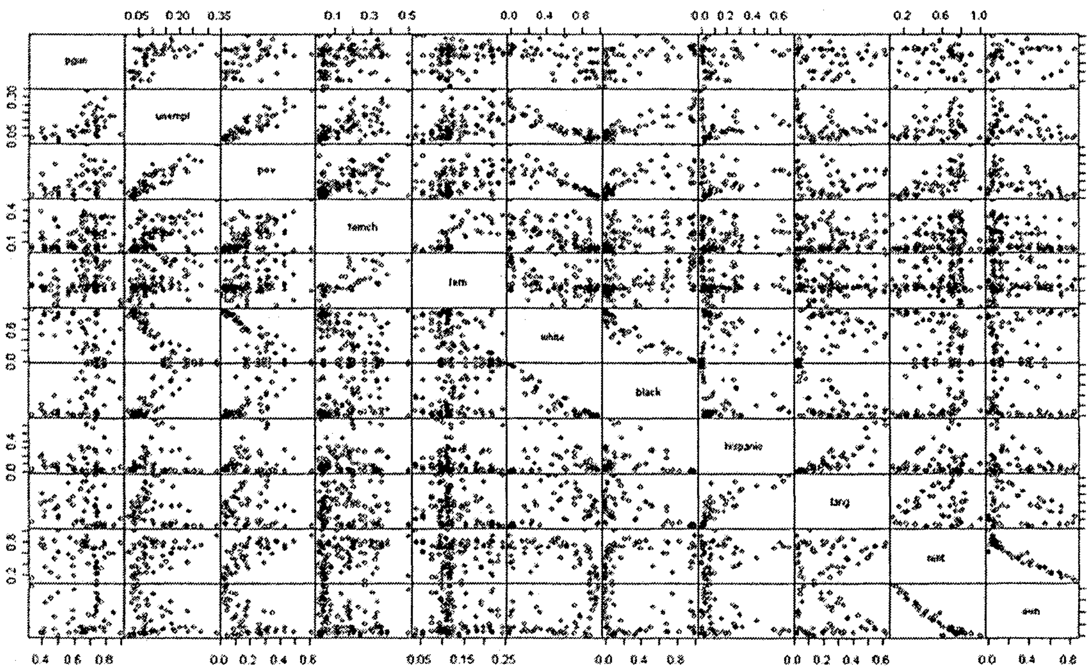
As outlined in Chapter 1, the 1990 Census neighborhood level variables are grouped into 4 main domains: racial layout, income, housing and social characteristics. This is illustrated in Table 3.

Table 3: 1990 Census Neighborhood Level Variables			
Racial	Income	Housing	Social Characteristic
% White	% Unemployment	% Own	% Female with children
% Black	% Poverty	% Rent	% Female with no children
% Hispanic			% Second language spoken at home

As expected, both the scatter plot (figure 5) and the correlation matrix (table 4) show that there is high collinearity within domains. For instance, OWN and RENT have a correlation of 96%. BLACK and WHITE have a correlation of 93%. Therefore, the predictors in the same domain can be used as proxies for one another since there is high collinearity within each of the domains.

Table 4: Correlation Matrix for Neighborhood-Level Variables											
	pgunz	unempl	pov	femch	fem	white	black	hispanic	lang	rent	own
pgunz	1										
unempl	0.50	1									
pov	0.28	0.86	1								
femch	0.41	0.90	0.94	1							
fem	0.39	0.69	0.43	0.62	1						
white	-0.57	-0.83	-0.67	-0.79	-0.80	1					
black	0.51	0.78	0.54	0.72	0.91	-0.93	1				
hispanic	0.10	-0.11	0.10	-0.08	-0.54	0.15	-0.49	1			
lang	-0.16	-0.39	-0.14	-0.35	-0.73	0.46	-0.75	0.88	1		
rent	-0.13	0.35	0.69	0.59	0.07	-0.31	0.14	0.21	0.15	1	
own	0.13	-0.25	-0.60	-0.48	0.05	0.20	-0.02	-0.32	-0.27	-0.96	1

Figure 5: Pairwise Plots for Suicide Data: Neighborhood Variables Only



Initial Model Selection, Response Variable: MORTAL

Appendix I displays the five best subsets based on AIC values for models with one neighborhood level variables, two neighborhood level variables, three neighborhood level variables and four neighborhood level variables. These are used as a starting point for model selection. When running all the possible models, it is apparent that HISPANIC as compared to the other races of BLACK and WHITE always results in a higher AIC. Therefore HISPANIC is removed as a neighborhood level predictor leaving only WHITE or BLACK in the racial layout domain. A series of logistic regression models are run on the remaining neighborhood level variables to determine if there is any collinearity between the census domains.

Using MORTAL, the likelihood of a suicide being fatal, as the binomial response (1 = individual dies, 0 = individual lives), each neighborhood level variable is regressed separately with the individual variables AGE, GENDER and METHOD. Next, pairs of neighborhood level variables are regressed onto MORTAL in order to determine the magnitude of collinearity between the neighborhood variables. Collinearity was assessed by comparing the value and sign of each coefficient in multi-variable models against the value and sign of each coefficient in the univariate results. Changes in sign and considerable changes in coefficient magnitude are both indications of collinearity. When WHITE and FEMCH are both regressed onto MORTAL, FEMCH is no longer significant to the model. The same happens when FEMCH is regressed onto MORTAL and BLACK is introduced into the model. This suggests collinearity among WHITE and FEMCH as well as BLACK and FEMCH. These findings are also supported by examining the scatter plot matrix and correlation matrix where BLACK and FEMCH have a correlation of 72% and WHITE and FEMCH 79%. BLACK and FEM have a high correlation of 92% with WHITE and FEM at 80%. Race is known to be a crucial variable in health outcomes. Therefore, race is left in the model, and FEM and FEMCH are excluded. The only neighborhood variable left from the social characteristics domain is LANG. When BLACK and LANG are both regressed onto MORTAL, LANG is no longer significant to the model. Therefore, LANG is removed from the model. Thus there will be no representation for the social characteristics domain since it is made up of the neighborhood level variables FEM, FEMCH and LANG.

When regressing both POV and BLACK, POV becomes insignificant to the model. When regressing both POV and WHITE onto MORTAL, the effect of the POV coefficient changes. This suggests high collinearity between POV and both WHITE and BLACK. Because race is more important to the model, POV will be removed as a neighborhood level variable. The other income domain variable is UNEMPL. The correlation between WHITE and UNEMPL is 83.5% and BLACK and UNEMPL is 78.3%. These factors suggest high collinearity among the race and the income domains. Since race is more important to the model, there is no neighborhood predictor for the income domain.

At this point 4 possible models remain. They are detailed in the following table.

Table 5: Possible Model Selections, Response Variable: MORTAL	
Possible Model Selection	AIC Value
BLACK, RENT, and PGUN	7217.2
BLACK, OWN, and PGUN	7213.4
WHITE, RENT, and PGUN	7217.3
WHITE, OWN, and PGUN	7211.3

Each model is made up of the two domains, race and housing, as well as neighborhood level gun availability. To pick the final model for the GLMM described in Chapter 4, the AIC value is used. The model with the lowest AIC value indicates the better model. Thus the final model contains the individual predictors AGE, GENDER and METHOD and neighborhood level predictors WHITE, OWN and PGUN.

Initial Model Selection, Response Variable: METHOD

Using METHOD as the binomial response (1 = suicide method is a firearm, 0 = suicide method is other), each neighborhood variable is regressed separately with the individual factors of AGE, GENDER, and MORTAL. When the individual neighborhood variables are regressed onto the response variable, METHOD, the results show that HISP, POV, RENT and OWN do not have a significant relationship with METHOD. Therefore, they are removed from the model. Next, pairs of neighborhood variables are regressed onto METHOD in order to determine the magnitude of collinearity between the remaining neighborhood variables. As explained in the previous section, changes in sign and considerable changes in coefficient magnitude are both indications of collinearity. Results from regressing both BLACK and FEMCH show that the effect of the FEMCH coefficient changes (correlation of 72%). When regressing WHITE and FEMCH onto METHOD, the effect of FEMCH changes (correlation of 79%). Regressing both FEM and BLACK onto METHOD results in BLACK no longer being significant to the model (correlation of 92%). The same results occur when introducing WHITE to the model, WHITE becomes insignificant (correlation of 80%). When both LANG and WHITE are introduced into the model, the magnitude of the

LANG coefficient changes. When regressing both BLACK and LANG onto METHOD, BLACK is no longer significant to the model. These are all signs of collinearity. Since race is more important, FEM, FEMCH and LANG are left out of the model. By removing FEM, FEMCH, and LANG as neighborhood predictors, there are no variable from the social characteristics domain in the final GLMM.

The remaining variables are the neighborhood level predictors of BLACK or WHITE for race and UNEMPL for income which results in two possible models. The first model is WHITE, UNEMPL and PGUN. The second model is BLACK, UNEMPL and PGUN. When both models are run using the logistic regression, UNEMPL is no longer significant to either model. Thus UNEMPL is removed as a neighborhood level predictor. That leaves race (WHITE or BLACK) and neighborhood level gun availability (PGUN).

Table 6: Possible Model Selections, Response Variable: METHOD	
Possible Model Selection	AIC Value
BLACK and PGUN	3392.4
WHITE and PGUN	3401.3

The model with neighborhood level predictors of BLACK and PGUN has the lowest AIC value. The final GLMM is made up of the individual variables AGE, GENDER and MORTAL and neighborhood level predictors BLACK and PGUN.

CHAPTER 4

GENERALIZED LINEAR MIXED MODELS

In Chapter 1, the importance of a random effect for the neighborhood when exploring the relationship various individual and neighborhood level variables have on the likelihood of choosing a firearm as the suicide method and the likelihood of a suicide being fatal is mentioned. Therefore, generalized linear mixed models are used to explore these relationships. To obtain the parameter estimates for each GLMM, a Bayesian approach using MCMC, specifically Gibbs sampling, is taken. This chapter starts with a review of MCMC methodology, and then provides an overview of model specification, convergence diagnostics and results for each GLMM.

Bayesian Approach with MCMC

The object of all Bayesian inference is the posterior distribution of the model parameters. Let D denote the observed data, and θ denote the model parameters. To determine the conditional distribution of θ on D, Bayes' theorem is used:

$$P(\theta|D) = \frac{P(\theta)P(D|\theta)}{\int P(\theta)P(D|\theta)d\theta}.$$

This is the posterior distribution of θ. In Bayesian inference, any elements of the posterior distribution such as moments and quantiles are recognized (Gilks et al., 1996).

These quantities can be expressed in terms of posterior expectations of functions of θ (Gilks et al., 1996). The posterior expectation of a function $f(\theta)$ is

$$E\left[f(\theta)\middle|D\right]=\frac{\int f(\theta)P(\theta)P(D|\theta)d\theta}{\int P(\theta)P(D|\theta)d\theta}. \tag{4.1}$$

In Bayesian inference, the integrations of this equation are difficult. In order to evaluate $E\left[f(\theta)\middle|D\right]$ one can use Monte Carlo integration, including MCMC (Gilks et al., 1996).

Markov Chain Monte Carlo

Let X be a vector of k random variables, with distribution $\pi(.)$ where X denotes the model parameters. Then equation (4.1) can be rewritten as

$$E\left[f(X)\right]=\frac{\int f(x)\pi(x)dx}{\int \pi(x)dx}.$$

Monte Carlo integration evaluates $E\left[f(X)\right]$ by approximating

$$E\left[f(X)\right]\approx\frac{1}{n}\sum_{t=1}^{n}f(X_t)$$

which is done by drawing samples $\{X_t, t=1,...,n\}$ from $\pi(.)$ (Gilks et al, 1996). Thus the population mean of $f(X)$ is estimated by the sample mean. If the samples $\{X_t, t=1,...,n\}$ are independent, due to the laws of large numbers the approximations can achieve desired accuracy by increasing the sample size n (Gilks et al, 1996). However, drawing samples $\{X_t, t=1,...,n\}$ independently from $\pi(.)$ is not practical since the form $\pi(.)$ is quite complicated (Gilks et al., 1996). Instead a Markov chain can be used.

The samples do not necessarily need to be independent as long as they are generated by any process which draws samples throughout the support of $\pi(.)$ in the correct proportions (Gilks et al., 1996). A method of doing this is by using a Markov chain having $\pi(.)$ as its stationary distribution. This then becomes Markov chain Monte Carlo.

A Markov chain is created by generating a sequence of random variables, $\{X_0, X_1, X_2,...\}$, such that at each time $t \geq 0$, the next state X_{t+1} is sampled from a transition distribution $P(X_{t+1}|X_t)$ which depends only on the current state of the chain, X_t (Gilks et al., 1996). The transition probability distributions must be constructed so that the Markov chain converges to a unique stationary distribution that is the posterior distribution, $\pi(.)$ (Gelman et al., 1995).

The Metropolis-Hastings Algorithm

Many methods have been designed for constructing and sampling from transition distributions for arbitrary posterior distributions. The Metropolis-Hastings algorithm is a general term for a family of Markov chain simulation methods that are useful for drawing samples from Bayesian posterior distributions (Gelman et al., 1995). The Metropolis-Hastings algorithm is developed by Metropolis et al. (1953) and subsequently generalized by Hastings (1970) (Chen et al., 2000).

Given a target distribution $\pi(\theta|D)$ that can be computed up to a normalizing constant, the Metropolis-Hastings algorithm creates a sequence of random points $(\theta_1, \theta_2, ...)$ whose distributions converge to the target distributions (Gelman et. al., 1995).

Let $q(\theta,\vartheta)$ be a proposal density such that $\int q(\theta,\vartheta)d\vartheta=1$. Also let $U(0,\ 1)$ denote the uniform distribution over (0, 1) (Chen et al., 2000). Then, a general version of the Metropolis-Hastings algorithm for sampling from the posterior distribution $\pi(\theta|D)$ can be described as follows (Chen et al., 2000):

Metropolis-Hastings Algorithm

Step 0. Choose an arbitrary starting point θ_0 and set $i=0$.

Step 1. Generate a candidate point θ^* from $q(\theta_i,\cdot)$ and u from $U(0,\ 1)$.

Step 2. Set $\theta_{i+1}=\theta^*$ if $u\le a(\theta_i,\theta^*)$ and $\theta_{i+1}=\theta_i$ otherwise, where the acceptance probability is given by

$$a(\theta,\vartheta)=\min\left\{\frac{\pi(\vartheta|D)q(\vartheta,\theta)}{\pi(\theta|D)q(\theta,\vartheta)},1\right\}. \tag{4.2}$$

Step 3. Set $i=i+1$, and go to Step 1.

The Metropolis-Hasting algorithm generalizes the basic Metropolis algorithm. The Metropolis algorithm considers only symmetric proposals, having the form $q(\theta,\vartheta)=q(\vartheta,\theta)$ for all θ and ϑ (Gilks et. al., 1996). For the Metropolis algorithm, the acceptance probability (4.3) becomes

$$a(\theta,\vartheta)=\min\left\{1,\frac{\pi(\vartheta|D)}{\pi(\theta|D)}\right\}.$$

When $q(\theta,\vartheta)=q(\vartheta)$, the Metropolis-Hastings algorithm becomes the independence chain Metropolis algorithm whose proposal $q(\theta,\vartheta)=q(\vartheta)$ does not depend on θ (Chen et al., 2000). For this the acceptance probability (4.3) can be written in the form

$$a(\theta,\vartheta)=\min\left\{1,\frac{\omega(\vartheta)}{\omega(\theta)}\right\},$$

where $\omega(\theta) = \frac{\pi(\theta)}{q(\theta)}$ (Gilks et. al., 1966). The Gibbs sampler is a special case of the Metropolis-Hastings algorithm obtained by choosing an appropriate $q(\theta, \vartheta)$ (Chen et al., 2000). For the Gibbs sampler the acceptance probability (4.3) is equal to one; that is, Gibbs sampler candidates are always accepted.

Gibbs Sampling

Suppose the parameter vector θ has been divided into d components or subvectors, $\theta = (\theta_1, ..., \theta_d)$. Gibbs sampling works by sampling from the conditional posterior density of each parameter given all the others and the data (Congdon, 2001; Gelman et al., 1995). At each iteration *t*, each θ_j^t is obtained by drawing from the following conditional distribution given all the other components of θ at their current values (Gelman et al., 1995; Congdon, 2001):

$$\pi\left(\theta_j^t \middle| \left(\theta_1^t, ..., \theta_{j-1}^t, \theta_{j+1}^{t-1}, ..., \theta_d^{t-1}\right), D\right).$$

Thus, each subvector θ_j is updated conditional on the latest value of θ for the other components (Gelman et al., 1995). The components at iteration *t* are already updated and components at *t-1* iterations have not yet been updated (Gelman et al., 1995). Such repeated sampling generates a dependent sequence of values, which subject to certain conditions, will eventually forget the starting value and converge to the stationary distribution $\pi(\theta|D)$, the posterior density (Congdon, 2001).

Convergence Diagnostics

The parameters of the GLMM's are not obtained by analytic solutions, therefore, it is very important to check and make sure convergence is achieved. To check for convergence another package called CODA (Convergence Diagnosis and Output Analysis Software for Gibbs sampling output) was applied. CODA is a program for analyzing the output of Markov Chain Monte Carlo (MCMC) simulations (Best et al., 1995).

CODA has several methods to determine convergence. The Geweke and Raftery & Lewis methods are selected for this study due to theoretical justification and ease of interpretation. Geweke (1992) introduced a convergence diagnostic based on standard time-series methods and should be used when interested in the convergence of a single chain. For each variable, the chain is divided into two "windows". One window contains the first x% (CODA default is 10%) and the other window holds the last y% (CODA default is 50%) of the iterates. If the whole chain is stationary, the means of the values early and late in the sequence should be similar. The sample mean and asymptotic variance is calculated for each window. Geweke's method uses a convergence diagnostic Z which is the difference between these two means divided by the asymptotic standard error of their difference. The idea is that as the iterations approach infinity, the sampling distribution of Z should approach a standard normal distribution if the chain has converged. If any values of Z fall into the extreme tails of a standard normal, then the chain was not fully converged early on (Best et. al., 1995).

The method of Raftery & Lewis specifies the number of iterations needed for each variable to reach convergence. Like Geweke's method it should also be used on single chains. The Raftery & Lewis convergence diagnostic reports the minimum number of iterations needed for each variable (Nmin) in order for Raftery & Lewis diagnostics to work, the total number of iterations that should be run for each variable (N) to obtain convergence, and the number of initial iterations to discard as the burn-in (M), all based on desired accuracy determined by the user. The burn-in is the number of iterations needed for the chain to 'forget' its starting position (Gilks et al., 1996)

GLMM, ResponseVariable: METHOD

The generalized linear mixed model considered for analyzing the relationship between the likelihood of choosing firearm as the suicide method and both individual and neighborhood level variables is as follows:

$$METHOD_{ij} \sim Binomial(1, p_{ij})$$

$$\text{logit}\left(p_{ij}\right) = \left(\beta_0 + \alpha_{0j}\right) + \left(\beta_1 + \alpha_{1j}\right) * AGE_{ij} + \left(\beta_2 + \alpha_{2j}\right) * AGE_{ij}^2 + \left(\beta_3 + \alpha_{3j}\right) * GENDER_{ij} + \left(\beta_4 + \alpha_{4j}\right) * MORTAL_{ij} + \beta_5 * PGUN_{ij} + \beta_6 * BLACK_{ij}$$

where i refers to the individual and j indexes the zip code. For the binomial response, $method_{ij}$, 1 indicates suicide by firearm and 0 indicates suicide by another method. A quadratic term for age is added to the model because of the potential for a non linear relationship of age with METHOD, the response. Because the response variable is dichotomous, a mixed-effects logistic regression model, a particular GLMM, is used. A mixed-effects logistic regression model is a common choice for analyzing multi-level dichotomous data (Everitt, 2005). It is assumed in this model that zip codes are independent.

The priors for the fixed effects $\beta_k(k = 5,6)$ follow a diffuse independent normal distribution with a mean of 0 and a precision of 0.05 so that $\beta_k(k = 5,6) \sim N(0,20)$. The $\alpha_{jk}(k = 0,1,...,4)$ are the random effects in the intercept and the slopes for AGE, AGE^2, GENDER, and MORTAL associated with the *j*th zip code. The $\beta_k(k = 0,1,..., 4)$ are the population average intercept and population average slope for AGE, AGE^2, GENDER, and MORTAL. The $\alpha_{kj}(k = 0,1,2,3,4)$ follow a multivariate normal with mean 0 and covariance $\sum$. The prior for $\beta_k\ (k = 0,1,2,3,4)$ is a vague multivariate normal with mean 0 and precision of 0.08, and $\tau = \sum^{-1}$ follows a Wishart distribution, $t \sim Wishart(R, \rho)$. The Wishart distribution is the conjugate prior for the inverse covariance matrix of a multivariate normal distribution. To represent vague prior knowledge, the degrees of freedom, ρ, is five, the rank of τ. The scale matrix R is specified as:

$$\begin{bmatrix} 0.01 & 0 & 0 & 0 & 0 \\ 0 & 0.01 & 0 & 0 & 0 \\ 0 & 0 & 0.01 & 0 & 0 \\ 0 & 0 & 0 & 0.01 & 0 \\ 0 & 0 & 0 & 0 & 0.01 \end{bmatrix}$$

Results, Response Variable: METHOD

The individual predictors in this model are age, gender and mortality. The neighborhood level predictors are gun availability and percent of black residents in the given zip code. Following the experiment, the 95% credible interval for the coefficient for percent of black residents is (0.9986, 1.0073). This means that the posterior probability that this coefficient lies in this interval is 0.95. For this study, it is decided that if an interval contains one then the parameter is no longer significant to the model. Therefore percent of black residents has no significant relationship with suicide method. Because of the importance of race in the literature percent of black residents is left in the model. The model parameter estimates after 2,500,000 iterations and a burn-in of 3,000 iterations are:

Table 7: GLMM Results, Response Variable: METHOD		
Variables	Parameter Estimates	95% Credible Interval
INTERCEPT	0.0166	(0.00114, 0.00235)
AGE	0.8396	(0.74297, 0.94848)
AGE^2	1.148	(1.0885, 1.2111)
GENDER	2.995	(2.3672, 3.8190)
MORTAL	153.55	(110.941, 218.77)
PGUN	1.0161	(1.0038, 1.0289)
BLACK	1.00298	(0.9986, 1.0073)

The results above show that males are 2.995 times more likely than females to choose firearm as the suicide method. For every percent increase in neighborhood level gun availability, an individual is 1.0161 times more likely to choose firearm over another method of suicide. Finally, a person who committed suicide is 153.55 times more likely than para-suicides to have chosen firearm as the suicide method.

Model Convergence, Response Variable: METHOD

Two diagnostic measures are Raftery & Lewis and Geweke's method. In Geweke's method, a thinning interval needs to be used since the number of iterations (2,500,000) is too large for the program to read. A thinning interval of ten is used which means that every tenth iteration out of the 2,500,000 iterations is drawn. The iterations are put into two groups, the first 25,000 iterations (10% of the iterations) and the last 125,000 iterations (50%). If the estimates are stable, the means of the values early and late in the sequence should be similar. Because Geweke's test takes the difference in the means from the two groups divided by the asymptotic standard error of their difference, as the iterations increase the sampling distribution Z should follow a standard normal. Thus the interest lies in the values of the sampling distribution that fall into the extreme tails of the standard normal distribution. Very few values fall outside the 95% confidence intervals. These results suggest convergence.

The second check for stability and convergence is the Raftery & Lewis diagnostic test which suggests the maximum number of iterations needed to obtain convergence. Results of this test on 25,000 iterations are displayed in Table 8. The lower bound states that a minimum of 3,746 iterations are needed to receive a correct output from the Raftery & Lewis diagnostics. This test is run on 25,000 iterations so the lower bound requirement is met. The results suggest a minimum of 2,340,900 iterations are needed in order for all parameter estimates to be stable and a minimum burn-in of 2,118 iterations. Our final run contains 2,500,000 iterations and estimates appear to have converged.

Table 8: Raftery & Lewis Diagnostics, Response Variable: METHOD

Variables	Burn-in (M)	Total Iterations (N)	Lower Bound (Nmin)
INTERCEPT	2118	2340900	3746
AGE	126	141414	3746
AGE^2	858	604812	3746
GENDER	264	280168	3746
MORTAL	408	381546	3746
PGUN	30	34512	3746
BLACK	30	31890	3746

GLMM with Interaction, Response Variable: METHOD

It may be the case that as neighborhood level gun availability (PGUN) increases or decreases, the effect of percent of black residents (BLACK) changes. Therefore, there is interest in seeing if an interaction term for the two neighborhood level predictors, gun availability and percent of black residents is significant to the model. The interaction term is significant to the model and neighborhood level gun availability is no longer significant to the model. However, PGUN is not removed from the model because the effect of PGUN at some other value of BLACK has a significant effect on METHOD since the interaction term is significant. Basically, PGUN has a fluctuating significance. The model parameter estimates after 1,500,000 iterations and a burn-in of 2000 are as follows:

Table 9: GLMM Results (with interaction), Response Variable: METHOD		
Variables	Parameter Estimates	95% Credible Interval
INTERCEPT	0.0012	(0.0004, 0.0032)
GENDER	2.9359	(2.3291, 3.7173)
AGE	0.8399	(0.7377, 0.9498)
AGE^2	1.149	(1.0885, 1.2145)
MORTAL	162.55	(114.549, 241.29)
PGUN	1.007	(0.9948, 1.0199)
BLACK	0.9688	(0.9449, 0.9394)
INTERACTION	1.0495	(1.0134, 1.0861)

Model (with Interaction) Convergence, Response Variable: METHOD

In Geweke's method, a thinning interval needs to be used since the number of iterations (1,500,000) is too large for the program to read. A thinning interval of six is used which means that every sixth iteration out of the 1,500,000 iterations is drawn. The iterations are put into two groups, the first 25,000 iterations (10% of the iterations) and the last 125,000 iterations (50%). If the estimates are stable, the means of the values early and late in the sequence should be similar. Because Geweke's test takes the difference in the means from the two groups divided by the asymptotic standard error of their difference, as the iterations increase the sampling distribution Z should follow a standard normal. Thus the interest lies in the values of the sampling distribution that fall into the extreme tails of the standard normal distribution. Very few values fall outside the 95% confidence intervals. These results suggest convergence.

The second check for stability and convergence is the Raftery & Lewis diagnostic. Results of this test on 25,000 iterations are displayed in Table 10. The lower bound states that a minimum of 3,746 iterations are needed to receive a correct output from the Raftery & Lewis diagnostics. This test is run on 25,000 iterations so the lower bound requirement is met. The results suggest a minimum of 1,035,315 iterations are needed in order for all parameter estimates to be stable and a minimum burn-in of 1,395 iterations. Our final run contains 1,500,000 iterations, and estimates appear to have converged.

Table 10: Raftery & Lewis Diagnostics, Response Variable: METHOD (Interaction)

Variables	Burn-in (M)	Total Iterations (N)	Lower Bound (Nmin)
INTERCEPT	378	412881	3746
AGE	80	95120	3746
AGE^2	72	79116	3746
GENDER	270	280764	3746
MORTAL	1395	1035315	3746
PGUN	16	19284	3746
BLACK	120	137584	3746
INTERACTION	136	129496	3746

GLMM, Response Variable: MORTAL

The generalized linear mixed model considered for analyzing the relationship between the likelihood of a suicide being fatal and both individual variables and neighborhood level variables is as follows:

$MORTAL_{ij} \sim Binomial(1, p_{ij})$

$$\text{logit}\left(p_{ij}\right)=\left(\beta_0+\alpha_{0j}\right)+\left(\beta_1+\alpha_{1j}\right)*AGE_{ij}+\left(\beta_2+\alpha_{2j}\right)*AGE_{ij}^2+\left(\beta_3+\alpha_{3j}\right)*GENDER_{ij}+$$
$$\left(\beta_4+\alpha_{4j}\right)*METHOD_{ij}+\beta_5*PGUN_{ij}+\beta_6*WHITE_{ij}+\beta_7*OWN_{ij}$$

where i refers to the individual and j indexes the zip code. For the binomial response, $MORTAL_{ij}$, 1 indicates completed suicide and 0 indicates para-suicide. A quadratic term for age is added to the model because of the potential for a non linear relationship of age with MORTAL, the response. Because the response variable is dichotomous, a mixed-effects logistic regression model, a particular GLMM, is used. It is assumed in this model that zip codes are independent.

The priors for the fixed effects $\beta_k\left(k=5,6,7\right)$ follow a diffuse independent normal distribution with a mean of 0 and a precision of 0.1, thus, $\beta_k\left(k=5,6,7\right)\sim N\left(0,10\right)$. The $\alpha_{jk}\left(k=0,1,\ldots,4\right)$ are the random effects in the intercept and the slopes for AGE, AGE ^{2}, GENDER, and METHOD associated with the jth zip code. The $\beta_k\left(k=0,1,\ldots,4\right)$ are the population average intercept and population average slope for AGE, AGE ^{2}, GENDER, and METHOD. The $\alpha_{kj}(k=0,1,2,3,4)$ follow a multivariate normal with mean 0 and covariance $\sum$. The prior for $\beta_k(k=0,1,2,3,4)$ is a vague multivariate normal with mean 0 and precision of 0.5, and $\tau=\sum^{-1}$ follows a Wishart distribution,

$t \sim Wishart(R, \rho)$. The Wishart distribution is the conjugate prior for the inverse covariance matrix of a multivariate normal distribution (Congdon, 2001). To represent vague prior knowledge, the degrees of freedom, ρ, is five, the rank of τ.

The scale matrix R is specified as:

$$\begin{bmatrix} 0.01 & 0 & 0 & 0 & 0 \\ 0 & 0.01 & 0 & 0 & 0 \\ 0 & 0 & 0.01 & 0 & 0 \\ 0 & 0 & 0 & 0.01 & 0 \\ 0 & 0 & 0 & 0 & 0.01 \end{bmatrix}$$

Results, Response Variable: MORTAL

The individual predictors in this model are age, gender, and suicide method. The neighborhood level predictors are gun availability, percent of white residents in the given zip code, and the percent of residents who own a home. In the model, neighborhood level gun availability (PGUN), percent of residents who own a home (OWN), and the quadratic term for age (AGE^2) are not significant to the model. The model parameter estimates after 1,000,000 iterations and a burn-in of 1,000 are:

Table 11: GLMM Results, Response Variable: MORTAL

Variables	Parameter Estimates	95% Credible Interval
INTERCEPT	0.111	(0.0184, 0.547)
AGE	2.001	(1.811, 2.212)
AGE^2	0.9604	(0.9137, 1.013)
GENDER	4.332	(3.728, 5.058)
METHOD	161.58	(112.505, 245.182)
PGUN	0.998	(0.9724, 1.022)
WHITE	1.0138	(1.005, 1.022)
OWN	0.99912	(0.9793, 1.002)

The results above show that males are 4.332 times more likely than females to commit suicide. The results also show that individuals who have chosen gun as their suicide method are 161.58 times more likely than others who choose a different suicide method to die. Finally, for every percentage increase of white residents in a neighborhood, an individual is 1.0138 times more likely to commit suicide. Current literature shows that whites commit suicide at a little more than 3 times the rates of blacks and hispanics. Both the results from the GLMM and current literature validate that being white increases the likelihood of a suicide being fatal.

Neighborhood level gun availability (PGUN) does not have an effect on the likelihood of a suicide being fatal. Figure 3 in Chapter 2 indicates that the relationship may not be linear. Therefore, it might be useful to try discretizing neighborhood level gun availability by using quantiles. Different quantiles could represent neighborhoods with differing gun availability. Two additional models are run. The first model divided PGUN into quartiles, and the other model used quintiles. Neither model shows any significant results between the quantiles and the likelihood of a suicide being fatal. Therefore it is concluded that there is no significant relationship between neighborhood level gun availability and the likelihood of a suicide being fatal.

Model Convergence, Response Variable: MORTAL

In Geweke's method, a thinning interval needs to be used since the number of iterations (1,000,000) is too large for the program to read. A thinning interval of four is used which means that every fourth iteration out of the 1,000,000 iterations is drawn. The iterations are put into two groups, the first 25,000 iterations (10% of the iterations) and the last 125,000 iterations (50%). If the estimates are stable, the means of the values early and late in the sequence should be similar. Because Geweke's test takes the difference in the means from the two groups divided by the asymptotic standard error of their difference, as the iterations increase the sampling distribution Z should follow a standard normal. Thus the interest lies in the values of the sampling distribution that fall into the extreme tails of the standard normal distribution. Very few values fall outside the 95% confidence intervals. These results suggest convergence.

The second check for stability and convergence is the Raftery & Lewis diagnostic. Results of this test on 25,000 iterations are displayed in Table 12. The lower bound states that a minimum of 3,746 iterations are needed to receive a correct output from the Raftery & Lewis diagnostics. This test is run on 25,000 iterations so the lower bound requirement is met. The results suggest a minimum of 619,329 iterations are needed in order for all parameter estimates to be stable and a minimum burn-in of 687. Our final run contained 1,000,000 iterations and estimates appear to have converged.

Table 12: Raftery & Lewis Diagnostics, Response Variable: MORTAL

Variables	Burn-in (M)	Total Iterations (N)	Lower Bound (Nmin)
INTERCEPT	12	16896	3746
AGE	78	99762	3746
AGE^2	30	37026	3746
GENDER	77	77451	3746
METHOD	687	619329	3746
PGUN	483	556807	3746
WHITE	168	194988	3746
OWN	60	66440	3746

Reparameterization

Reparameterization often speeds up convergence by reducing dependence between parameters. The neighborhood level variables are reparameterized by centering them around their means. Reparameterization significantly sped up the programs and aided in faster convergence.

For example, the general linear mixed model for METHOD with no interaction:

$$METHOD_{ij} \sim Binomial(1, p_{ij})$$

$$\text{logit}\left(p_{ij}\right) = \left(\beta_0 + \alpha_{0j}\right) + \left(\beta_1 + \alpha_{1j}\right) * AGE_{ij} + \left(\beta_2 + \alpha_{2j}\right) * AGE_{ij}^2 + \left(\beta_3 + \alpha_{3j}\right) * GENDER_{ij} + \left(\beta_4 + \alpha_{4j}\right) * MORTAL_{ij} + \beta_5 * PGUN_{ij} + \beta_6 * BLACK_{ij}$$

where i refers to the individual and j indexes the zip code is first run without reparameterization and then after reparameterizing. Table 13 displays the Raftery & Lewis diagnostics for the original variables and Table 14 shows the Raftery & Lewis diagnostics for the reparameterized variables. The total iterations for PGUN before reparameterizing are 1,068,408. After reparameterization they are 34,512 total iterations. It's important to note that the total number of iterations needed for all variables increased after reparameterization. So reparameterization did not decrease the overall total number of iterations needed, but it did speed up the program.

Table 13: Raftery & Lewis Diagnostics for Original Variables			
Variables	Burn-in (M)	Total Iterations (N)	Lower Bound (Nmin)
INTERCEPT	1518	1633690	3746
AGE	217	235631	3746
AGE^2	190	203414	3746
GENDER	504	499128	3746
MORTAL	637	687470	3746
PGUN	988	1068408	3746
BLACK	66	99330	3746

Table 14: Raftery & Lewis Diagnostics for Reparameterized Variables			
Variables	Burn-in (M)	Total Iterations (N)	Lower Bound (Nmin)
INTERCEPT	2118	2340900	3746
AGE	126	141414	3746
AGE^2	858	604812	3746
GENDER	264	280168	3746
MORTAL	408	381546	3746
PGUN	30	34512	3746
BLACK	30	31890	3746

Starting Values and Choice of Priors

The research on starting values shows that it is seldom necessary to spend much effort in choosing starting values (Gilks et al, 1996). A chain that converges quickly will find its way from extreme starting values rapidly. If a chain is slow-mixing starting values may need to be chosen more carefully to avoid a lengthy burn-in (Gilks et al., 1996)

The priors initially used for the fixed and random effects are described above in the GLMM sections for each response. Additional models are run with flatter priors. Flatter priors achieve the same parameter estimates and standard errors. This implies that the priors in the models are virtually non-informative.

CHAPTER 5

MENTAL DISORDERS AND SUICIDE

Current research shows mental disorders and substance-abuse disorders are risk factors for suicide (NIMH, 2007). More than 90% of people who die from suicide suffer from a mental disorder, substance-abuse disorder, or both (Moscicki, 1997). Another objective of this paper is to determine if para-suicides with a mental disorder are more likely than para-suicides without a mental disorder to use a firearm to attempt suicide. As stated in Chapter 1, 81% of para-suicides are associated with a mental disorder. The most prevalent mental disorders among para-suicides are depression (42%), drug psychoses or dependence (22%), and adjustment reaction disorder (13%).

Table 15: Contingency Table for Para-suicides and Suicide Method

	Suicide Method		
Group	Firearm	Other	Total
Para-suicides with a mental disorder	21	8,474	8,495
Para-suicides without a mental disorder	17	1,945	1,962
Total	10,419	38	10,457

To determine if para-suicides with a mental disorder are more likely than para-suicides without a mental disorder to attempt suicide by firearm a Chi-Square test is used.

The results show that para-suicides with a mental disorder are less likely than para-suicides without a mental disorder to use a firearm to attempt suicide ($p < 0.001$).

CHAPTER 6

DISCUSSION AND CONCLUSIONS

This study has three objectives:

1. Explore the relationship that various individual level and neighborhood level predictors have on the likelihood of choosing firearm as the method of suicide. In particular, determine if neighborhood level gun availability has a significant effect on the likelihood of choosing firearm as the suicide method.
2. Explore the relationship that various individual level and neighborhood level predictors have on the likelihood of a suicide being fatal. More importantly, determine if neighborhood level gun availability has a significant effect on the likelihood of a suicide being fatal.
3. Determine if para-suicides (i.e., attempted suicides) with a mental disorder are more likely than para-suicides without a mental disorder to use a firearm to attempt suicide.

For the first objective, a GLMM is used to explore the relationship described. Initial model selection is carried out using a series of logistic regression models and AIC values. The final GLMM consisted of individual level and neighborhood level predictors. The individual level predictors consisted of age, gender, and mortality. The neighborhood level predictors are percent of black residents and neighborhood level gun availability. A

Bayesian approach using MCMC, specifically Gibbs sampling, is used to obtain the parameter estimates for the GLMM. Results show that males are 2.995 times more likely than females to choose a firearm as the suicide method. Also, for every percent increase in neighborhood level gun availability, an individual is 1.0161 times more likely to choose firearm over another method, and a person who committed suicide is 153.55 times more likely than para-suicides to choose firearm as the suicide method.

The method used in evaluating objective 2 is analogous to objective 1. The final GLMM is composed of age, gender, method of suicide, percent of white residents, percent of residents who own a home, and neighborhood level gun availability. The results show that males are 4.332 times more likely than females to successfully commit suicide. Also, individuals who choose suicide by firearm are 161.58 times more likely than others who choose another suicide method to perish. In addition, for every percent increase in white residents, an individual is 1.0138 times more likely to die from suicide. Neighborhood level gun availability has no effect on the likelihood of a suicide being fatal. It may be that the relationship between neighborhood level gun availability and the likelihood of a suicide being fatal may not be linear. Therefore, neighborhood level gun availability is discretized using quantiles, and two additional GLMM'S are run. One model discretizes by using quartiles and the other uses quintiles. Neither model shows any significance between the quantiles and the likelihood of a suicide being fatal. Therefore, it's concluded that there is no significant relationship between neighborhood level gun availability and the likelihood of a suicide being fatal.

For the third objective, a Chi-Square test is used. It is concluded that para-suicides with a mental disorder are less likely than para-suicides without a mental disorder to choose a firearm to attempt suicide (OR 0.284, 95% CI 0.155 to 0.517).

Study Limitations and Future Work

In this analysis zip codes are assumed independent. Future work could explore the possibilities of relaxing this assumption as in Mollié (Mollié et al., 1991). In the future it may be useful to look at neighborhoods based on a smaller spectrum, such as census tracts, instead of zip codes. However, for this study data are only available on the zip code level.

A limitation for this study is the possibility of incomplete counts and misclassification. Undoubtedly a considerable number of suicides resulted in neither death nor hospitalization. These cases are not included in this study. It's possible the list of completed suicides is also incomplete. One reason could be that a completed suicide is diagnosed as an accidental discharge. As stated in Chapter 1, information on admissions to psychiatric hospitals and V.A. hospitals is not available for this study. Therefore, para-suicides from these sources are not included in this study. However, successful attempts are included which inflates the proportion of lethal cases. This inflation may be considerable, given that a large number of suicides occur in psychiatric hospitals (Achte et al., 1969; Harris et al., 1997; Shenassa et al., 2003).

APPENDIX I

BEST SUBSET MODELS

Five Best 1 Neighborhood Variable Models (based on lowest AIC)

Variable	Parameter Estimate	P-value	95% CI	AIC
Intercept	0.034068	< 2E-16	(0.0256, 0.0447)	
Age	1.045244	< 2E-16	(1.041, 1.049)	
Gender	4.322786	< 2E-16	(3.80, 4.92)	7,243.70
Method	148.811440	< 2E-16	(105.689, 209.527)	
% Female with no children	0.925485	< 2E-16	(0.912, 0.939)	

Variable	Parameter Estimate	P-value	95% CI	AIC
Intercept	0.017065	< 2E-16	(0.0140, 0.0208)	
Age	1.044461	< 2E-16	(1.041, 1.048)	
Gender	4.352725	< 2E-16	3.819, 4.955)	7,244.50
Method	146.973309	< 2E-16	(104.44, 206.84)	
% Black	0.990637	< 2E-16	(0.989, 0.992)	

Variable	Parameter Estimate	P-value	95% CI	AIC
Intercept	0.007668	< 2E-16	(0.0063, 0.0094)	
Age	1.043990	< 2E-16	(1.040, 1.048)	
Gender	4.350205	< 2E-16	(3.819, 4.955)	7,256.90
Method	142.369672	< 2E-16	(101.29, 200.10)	
% White	1.009933	< 2E-16	(1.008, 1.012)	

Variable	Parameter Estimate	P-value	95% CI	AIC
Intercept	0.007668	< 2E-16	(0.0063, 0.0094)	
Age	1.043990	< 2E-16	(1.040, 1.048)	
Gender	4.350205	< 2E-16	(3.82, 4.95)	7,265.20
Method	142.369672	< 2E-16	(101.29, 200.10)	
%Unemployment	0.952195	< 2E-16	(0.943, 0.962)	

Variable	Parameter Estimate	P-value	95% CI	AIC
Intercept	0.007668	< 2E-16	(0.0063, 0.0094)	
Age	1.043990	< 2E-16	(1.040024, 1.047972)	
Gender	4.350205	< 2E-16	(3.819446, 4.954719)	7,275.20
Method	142.369672	< 2E-16	(101.2933, 200.1032)	
Neighborhood Level Gun Availability	0.977624	< 2E-16	(0.9730975, 0.9821728)	

Five Best 2 Neighborhood Variable Models (based on lowest AIC)

Variable	Parameter Estimate	P-value	95% CI	AIC
Intercept	0.072863	< 2E-16	(0.0504, 0.1054)	7,213.70
Age	1.044474	< 2E-16	(1.040516, 1.048446)	
Gender	4.329967	< 2E-16	(3.800925, 4.932644)	
Method	151.942780	< 2E-16	(107.8955, 213.9720)	
Neighborhood Level Gun Availability	0.985588	< 0.001	(0.9807, 0.9905)	
% Female with no children	0.940344	< 0.001	(0.92591, 0.9550)	

Variable	Parameter Estimate	P-value	95% CI	AIC
Intercept	0.008793	< 2E-16	(0.00716, 0.01079)	7,214.80
Age	1.044158	< 2E-16	(1.040181, 1.048150)	
Gender	4.354179	< 2E-16	(3.822312, 4.960052)	
Method	155.108055	< 2E-16	(110.0344, 218.6455)	
% White	1.011785	< 2E-16	(1.009750, 1.013823)	
% Own	0.990293	< 0.001	(0.9874, 0.9932)	

Variable	Parameter Estimate	P-value	95% CI	AIC
Intercept	0.003688	< 2E-16	(0.00270, 0.005046)	7,219.20
Age	1.044033	< 2E-16	(1.040060, 1.048022)	
Gender	4.340376	< 2E-16	(3.810428, 4.944030)	
Method	155.156766	< 2E-16	(110.0486, 218.7545)	
% White	1.012475	< 2E-16	(1.010356, 1.014600)	
% Rent	1.010438	< 0.001	(1.007136, 1.013751)	

Variable	Parameter Estimate	P-value	95% CI	AIC
Intercept	0.032407	< 2E-16	(0.0253, 0.0415)	7,220.70
Age	1.044688	< 2E-16	(1.040708, 1.048681)	
Gender	4.347618	< 2E-16	(3.816827, 4.952224)	
Method	150.699080	< 2E-16	(107.0422, 212.1614)	
% Own	0.986182	< 2E-16	(0.9831, 0.9893)	
% Female with children under 18 years of age	0.962994	< 2E-16	(0.95657, 0.9695)	

Variable	Parameter Estimate	P-value	95% CI	AIC
Intercept	0.009884	< 2E-16	(0.00758, 0.01289)	7,222.80
Age	1.044499	< 2E-16	(1.040523, 1.048491)	
Gender	4.327833	< 2E-16	(3.799752, 4.929304)	
Method	151.039441	< 2E-16	(107.2712, 212.6657)	
% Rent	1.016148	< 2E-16	(1.012438, 1.019871)	
% Female with children under 18 years of age	0.958866	< 2E-16	(0.952, 0.9658)	

Five Best 3 Neighborhood Variable Models (based on lowest AIC)

Variable	Parameter Estimate	P-value	95% CI	AIC
Intercept	0.016046	< 2E-16	(0.0104, 0.02465)	
Age	1.044054	< 2E-16	(1.040072, 1.048050)	
Gender	4.360536	< 2E-16	(3.827605, 4.967666)	
Method	153.781383	< 2E-16	(109.1525, 216.6578)	7,207.10
% White	1.007096	< 0.001	(1.003544, 1.010660)	
% Own	0.987982	< 0.001	(0.9847, 0.99123)	
% Female with children under 18 years of age	0.981941	0.0021	(0.9706, 0.9934)	

Variable	Parameter Estimate	P-value	95% CI	AIC
Intercept	0.005642	< 2E-16	(0.00384, 0.00830)	
Age	1.043878	< 2E-16	(1.039900, 1.047871)	
Gender	4.343068	< 2E-16	(3.812513, 4.947459)	
Method	154.338617	< 2E-16	(109.5290, 217.4804)	7,208.40
% White	1.007226	< 0.001	(1.003694, 1.010770)	
% Rent	1.014074	< 0.001	(1.010224, 1.017938)	
% Female with children under 18 years of age	0.978518	< 0.001	(0.9668, 0.9904)	

Variable	Parameter Estimate	P-value	95% CI	AIC
Intercept	0.073862	< 2E-16	(0.0510, 0.10697)	
Age	1.044860	< 2E-16	(1.040885, 1.048850)	
Gender	4.324437	< 2E-16	(3.796043, 4.926378)	
Method	155.127910	< 2E-16	(110.0901, 218.5907)	7,209.30
Neighborhood Level Gun Availability	0.986435	< 0.001	(0.9815, 0.99143)	
% Own	0.996393	0.0120	(0.9936, 0.9992)	
% Female with no children	0.940587	< 0.001	(0.9262, 0.9551)	

Variable	Parameter Estimate	P-value	95% CI	AIC
Intercept	0.027121	< 2E-16	(0.020776, 0.03540)	
Age	1.044564	< 2E-16	(1.040587, 1.048558)	
Gender	4.347665	< 2E-16	(3.816568, 4.952672)	
Method	153.889837	< 2E-16	(109.1806, 216.9075)	7,209.60
% Own	0.989481	< 0.001	(0.9859, 0.9931)	
% Poverty	1.030431	< 0.001	(1.013878, 1.047255)	
% Female with children under 18 years of age	0.933637	< 0.001	(0.9169, 0.9507)	

Variable	Parameter Estimate	P-value	95% CI	AIC
Intercept	0.033400	< 2E-16	(0.0245, 0.04554)	
Age	1.044123	< 2E-16	(1.040145, 1.048116)	
Gender	4.348252	< 2E-16	)3.816958, 4.953502)	
Method	155.679748	< 2E-16	(110.4151, 219.5007)	7,210.20
% Black	0.986501	< 2E-16	(0.9841, 0.98896)	
% Own	0.991060	< 0.001	(0.9881, 0.9941)	
% Other language spoken at home	0.989420	< 0.001	(0.9847, 0.9942)	

Five Best 4 Neighborhood Variable Models (based on lowest AIC)

Variable	Parameter Estimate	P-value	95% CI	AIC
Intercept	0.014654	< 2E-16	(0.00954, 0.0225)	7,198.60
Age	1.043977	< 2E-16	(1.039995, 1.047973)	
Gender	4.355311	< 2E-16	(3.822935, 4.961824)	
Method	156.608177	< 2E-16	(111.0594, 220.8378)	
% White	1.006459	< 0.001	(1.002911, 1.010018)	
% Own	0.990710	< 0.001	(0.9871, 0.9944)	
% Poverty	1.027905	0.0012	(1.010978, 1.045115)	
% Female with children under 18 years of age	0.952442	< 0.001	(0.932, 0.9732)	

Variable	Parameter Estimate	P-value	95% CI	AIC
Intercept	0.006554	< 2E-16	(0.00441, 0.00973)	7,200.70
Age	1.043846	< 2E-16	(1.039868, 1.047840)	
Gender	4.342473	< 2E-16	(3.811858, 4.946952)	
Method	156.545703	< 2E-16	9111.0214, 220.7373)	
% White	1.006604	< 0.001	(1.003072, 1.010149)	
% Rent	1.010699	< 0.001	(1.006312, 1.015105)	
% Poverty	1.027086	0.0019	(1.009908, 1.044557)	
% Female with children under 18 years of age	0.951031	< 0.001	(0.931, 0.9716)	

Variable	Parameter Estimate	P-value	95% CI	AIC
Intercept	0.041572	< 2E-16	(0.02844, 0.06076162)	7,202.40
Age	1.044326	< 2E-16	(1.040345, 1.048323)	
Gender	4.341383	< 2E-16	(3.810827, 4.945810)	
Method	154.658893	< 2E-16	(109.7446, 217.9547)	
Neighborhood Level Gun Availability	0.991296	0.0023	(0.9857, 0.99689)	
% Own	0.991515	< 0.001	(0.98771, 0.99534)	
% Female with children under 18 years of age	0.940740	< 0.001	(0.92298, 0.95885)	
% Poverty	1.029133	< 0.001	(1.012370, 1.046174)	

Variable	Parameter Estimate	P-value	95% CI	AIC
Intercept	0.024708	< 2E-16	(0.01371, 0.04452)	7,204.80
Age	1.044003	< 2E-16	(1.040019, 1.048002)	
Gender	4.353887	< 2E-16	(3.821634, 4.960271)	
Method	153.844446	< 2E-16	(109.2152, 216.7110)	
Neighborhood Level Gun Availability	0.993662	0.0369	(0.9877, 0.99961)	
% Own	0.989259	< 0.001	(0.9858, 0.9927)	
% Female with children under 18 years of age	0.983017	0.0038	(0.9717, 0.9945)	
% White	1.005788	0.0024	(1.002043, 1.009547)	

Variable	Parameter Estimate	P-value	95% CI	AIC
Intercept	0.033414	< 2E-16	(0.01608, 0.0694)	7,205.10
Age	1.044314	< 2E-16	(1.040324, 1.048319)	
Gender	4.340272	< 2E-16	(3.809698, 4.944735)	
Method	156.388454	< 2E-16	(110.9349, 220.4658)	
Neighborhood Level Gun Availability	0.990680	0.0026	(0.9847, 0.9967)	
% Own	0.993864	< 0.001	(0.9904, 0.99733)	
% Female with no children	0.964283	0.0043	(0.941, 0.989)	
% White	1.005202	0.0132	(1.001, 1.0093)	

APPENDIX II

WINBUGS PROGRAM, RESPONSE VARIABLE: METHOD

```
model{
 for (i in 1:N) {
   method[i] ~ dbin(p[i], 1);
  logit(p[i]) <-  alpha[zip[i],1] + alpha[zip[i],2]*gender[i]+ alpha[zip[i],3]*age[i] + alpha[zip[i],4]*age2[i]
                  +  alpha[zip[i],5]*mortal[i] + beta[1]*pgun[i]+ beta[2]*black[i]
   method.hat[i] <- p[i] # fitted values
 }

# Priors for fixed effects:
for (k in 1:2) {
     beta[k] ~dnorm(0, .05)
     }

 # Priors for random coefficients:
  for (j in 1:M) {
    alpha[j,1:5] ~dmnorm(mu[1:5], tau[1:5,1:5])
  }

mu[1:5] ~ dmnorm(mean[1:5], prec[1:5,1:5])
 tau[1:5,1:5] ~ dwish(R[1:5,1:5],5)
 sigma2[1:5,1:5] <- inverse(tau[1:5,1:5])


}
list(N=12701, M=53,
mean = c(0, 0, 0, 0, 0),
R = structure(.Data = c(0.01, 0, 0, 0, 0,
                                0, 0.01, 0, 0, 0,
                                0, 0, 0.01, 0, 0,
                                0, 0, 0, 0.01, 0,
                                0, 0, 0, 0, 0.01),
                          .Dim = c(5, 5)),
prec = structure(.Data = c(0.08, 0, 0, 0, 0,
                                0, 0.08, 0, 0, 0,
                                  0, 0, 0.08, 0, 0,
                                  0, 0, 0, 0.08, 0,
                                   0, 0, 0, 0, 0.08),
                             .Dim = c(5, 5)),
```

Data for method, gender, zip, age, age ^{2} , mortal, pgun, and black)

APPENDIX III

WINBUGS PROGRAM, RESPONSE VARIABLE: METHOD (INTERACTION)

```
model{
 for (i in 1:N) {
   method[i] ~ dbin(p[i], 1);
  logit(p[i]) <-  alpha[zip[i],1] + alpha[zip[i],2]*gender[i]+ alpha[zip[i],3]*age[i] +
                  alpha[zip[i],4]*age2[i]  + alpha[zip[i],5]*mortal[i] + beta[1]*pgun[i]+
                  beta[2]*black[i] + beta[3]*inter[i]
   method.hat[i] <- p[i] # fitted values bet
 }

# Priors for fixed effects:
for (k in 1:3) {
     beta[k] ~dnorm(0, .1)
     }

# Priors for random coefficients:
  for (j in 1:M) {
    alpha[j,1:5] ~dmnorm(mu[1:5], tau[1:5,1:5])
  }

mu[1:5] ~ dmnorm(mean[1:5], prec[1:5,1:5])
 tau[1:5,1:5] ~ dwish(R[1:5,1:5],5)
 sigma2[1:5,1:5] <- inverse(tau[1:5,1:5])

}
list(N=12701, M=53,
mean = c(0, 0, 0, 0, 0),
R = structure(.Data = c(0.01, 0, 0, 0, 0,
                        0, 0.01, 0, 0, 0,
                        0, 0, 0.01, 0, 0,
                        0, 0, 0, 0.01, 0,
                        0, 0, 0, 0, 0.01),
                  .Dim = c(5, 5)),
prec = structure(.Data = c(0.5, 0, 0, 0, 0,
                           0, 0.5, 0, 0, 0,
                             0, 0, 0.5, 0, 0,
                             0, 0, 0, 0.5, 0,
                              0, 0, 0, 0, 0.5),
                         .Dim = c(5, 5)),
```

Data for method, zip, age, age ^{2} , gender, mortal, pgun, black, inter)

APPENDIX IV

WINBUGS PROGRAM, RESPONSE VARIABLE: MORTAL

```
model{
 for (i in 1:N) {
   mortal[i] ~ dbin(p[i], 1);
  logit(p[i]) <-  alpha[zip[i],1] + alpha[zip[i],2]*sex[i] + alpha[zip[i],3]*age[i] +
                  alpha[zip[i],4]*age2[i] + alpha[zip[i],5]*method[i] + beta[1]*pgun[i] +
                  beta[2]*white[i] + beta[3]*own[i]
  mortal.hat[i] <- p[i] # fitted values
 }

# Priors for fixed effects:
for (k in 1:3) {
     beta[k] ~dnorm(0, .1)
     }

# Priors for random coefficients:
  for (j in 1:M) {
    alpha[j,1:5] ~dmnorm(mu[1:5], tau[1:5,1:5])
  }

mu[1:5] ~ dmnorm(mean[1:5], prec[1:5,1:5])
 tau[1:5,1:5] ~ dwish(R[1:5,1:5],5)
 sigma2[1:5,1:5] <- inverse(tau[1:5,1:5])

}
list(N=12701, M=53,
mean = c(0, 0, 0, 0, 0),
R = structure(.Data = c(0.01, 0, 0, 0, 0,
                        0, 0.01, 0, 0, 0,
                        0, 0, 0.01, 0, 0,
                        0, 0, 0, 0.01, 0,
                        0, 0, 0, 0, 0.01),
              .Dim = c(5, 5)),
prec = structure(.Data = c(0.5, 0, 0, 0, 0,
                           0, 0.5, 0, 0, 0,
                           0, 0, 0.5, 0, 0,
                           0, 0, 0, 0.5, 0,
                           0, 0, 0, 0, 0.5),
                 .Dim = c(5, 5)),
```

Data for mortal, zip, age, age ^{2}, gender, method, pgun, black, inter)

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