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Looking Upstream: A Sociological Investigation of Mass Public Shootings

Joel A. Capellan
The Graduate Center, City University of New York

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Joel Alfredo Capellan
Department of Criminal Justice

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by

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This manuscript has been read and accepted for the Graduate Faculty in Criminal Justice in satisfaction of the dissertation requirement for the degree of Doctor of Philosophy.

Jeremy R. Porter, Ph.D.

Date | Chair of Examining Committee

Deborah Koetzle, Ph.D.

Date | Executive Officer

Supervisory Committee:

Jeremy R. Porter, Ph.D.

Amy Adamzyck, Ph.D.

Joshua Freilich, Ph.D.

Abstract

In the last 40 years, social scientists have provided important insights into the different characteristics of mass public shootings: their prevalence, types, patterns, and individual risk factors. However, we still lack a fundamental understanding of the processes that shape its incidence and spatial distribution. Our failure to tap into these dynamics is rooted in our inability to escape the dominant paradigm in which this phenomenon has been examined. Literature on mass murders, and most recently on mass public shootings, has been trapped by an analytical framework that cares only for individual risk factors. This paradigm is myopic because it assumes that only the proximate causes (i.e., factors and events closest to the attack) shape the prevalence and distribution of such attacks.

The goal of this study is to step away from this paradigm and recast these shootings as a social phenomenon, shaped by social forces. This investigation is couched on three major Sociological/Criminological theoretical perspectives: social integration, social disorganization, and imitation/diffusion theories. Under social integration/social disorganization theory, I posit that certain ecological characteristics (primarily low social cohesion) make certain populations more at risk or vulnerable to these types of massacres. Similarly, I argue that an imitation or diffusion process, driven primarily by media exposure, also shapes the incidence and spatial distribution of these attacks.

A Continuous-time Event History Model (or Hazard/Survival Model) is used to test the influence of social integration and imitation/diffusion forces on the prevalence of mass public shootings in the contiguous United States for the 1970-2014 time period. The results paint a mixed, but rather interesting picture. From the theoretical perspective findings are mixed.

Imitation/diffusion and social disorganization theory were not supported by the results. Durkheim's social integration theory was the most successful, but also partially supported.

Despite these mixed findings, the results provide unexpected and interesting insights into the social causes of mass public shootings. The findings show that (contrary to expectations) the occurrence of a mass public shooting was found to depress the odds of future attacks. We also learned that mass public shootings tend occur in states that are more rural, with greater levels of marriage stability, and social-economic status. These are quite unique findings, as these relationships tend to be reversed for regular homicide. The results suggest that mass public shootings behave more like suicide, than regular homicide. This study is the first to provide insights into the sociological roots of mass public shootings. As such, the results provide a springboard for the future literature.

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Like all things, this dissertation is a collaborative endeavor. It represents not only the work I have put into my doctoral studies the past five years, but equally as important, the work the faculty, administrative staff, family, and friends have put in towards my education and well-being. Suffice it to say, this would have not been possible without all of you.

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CHAPTER 1
INTRODUCTION

On December 14th, 2012, Adam Lanza shot his mother four times in the head while she slept at their home in Newtown. He then headed toward the Sandy Hook Elementary School. Using his mother's Bushmasters XM15 rifle, Lanza shot his way through the front door of his former school. Wearing an all-black uniform, yellow earplugs, and additional weapons, Lanza entered the classroom of first-grade teacher Victoria Soto and immediately began firing. Lanza moved from classroom to classroom firing at everyone he encountered. The relentless shooting ended when the gunman shot himself in the head 11 minutes after he started the attack. By then, however, the damage was done. Adam Lanza had killed 27 people and injured two others.

In the wake of the attack, everyone struggled to come to terms with what seemed a senseless massacre. For a brief moment, before the discourse devolved into a gun control versus gun rights argument, people asked the right questions. How can such a massacre occur in a beautiful small town like Sandy Hook? What could drive Adam Lanza to commit such a massacre? Why were homicides followed by suicides? Are such "random" mass shootings becoming the new normal? Is it possible to predict or prevent these mass public shootings? Expert comments to these questions were as usual; they were as strikingly similar as they were dissatisfactory. Nothing about the attack or Adam Lanza himself reveals anything new or unique (Fox, 2013). Everything from Lanza's personal characteristics, social marginalization, struggles with mental health, to the way he planned, conducted, and concluded the attack, fits the typical mass public shooting profile. Yet, there is not possible to predict or explain why mass public shootings occur.

A prediction involves a statement of what will happen or is likely to happen in the future, and it implies a clear understanding of the dynamics that shape the incidence and distribution of the phenomenon. Over the last 40 years, social scientists have identified a number of recurring patterns and factors that contribute to mass murders in general and mass public shootings in particular. However, while it appears that we are aware of all the relevant factors, we are unable to put them together. In other words, we lack a fundamental understanding of how individual risk factors contribute to the incidence and distribution of mass public shootings in the United States. If we are to obtain new insights into this phenomenon, we need to reevaluate the paradigm used to study these massacres and consider new perspectives.

In this study, I set aside the assumption that massacres are shaped only by *proximate causes* (i.e., the factors closest to the event). Instead of seeing mass public shootings as an individual-level phenomenon, I interpret these attacks as a social phenomenon subject to social forces. A discussion on the nature of mass public shootings suggests that these acts are not just murder but also suicide. Accordingly, this sociological examination of mass public shootings is grounded on three theoretical frameworks linked to suicide and murder: Durkheim's theory of social integration, Shaw & McKay's social disorganization theory and Tarde's theory of imitation. The observable implications of these theories are tested using the continuous-time Event History Analysis (EHA) framework with failure-time as the dependent variable.

This study makes several contributions to the mass murder literature. This is the first study to treat mass public shootings as a social phenomenon and formulate and test sociological theories to explain its incidence and distribution in the United States. This is the first study that considers the murderous and suicidal natures of mass public shootings and adopts a theoretical framework that may account for both processes. This study employs the most comprehensive database on mass public shootings in the United States. Most importantly, this study is the first to use multivariate statistics to model the hypothesized social processes that lead to mass public shootings. Collectively, this study attempts to bring novel insights into a phenomenon that is full of myths and misconceptions.

CHAPTER 2
OVERVIEW OF THE LITERATURE

There is considerable overlap between mass public shootings and mass murders as the former is a subtype of the latter. As a result, mass public shootings and mass murders are intrinsically linked. In last 40 years, however, researchers have focused largely on the umbrella concept of mass murder, thereby lumping different types of mass homicides together (Bowers, Holmes, & Rohm, 2010; Delisi & Scherer, 2006; Duwe, 2000, 2004, 2006; Fox & Levin, 1998, 2003, 2012; Levin & Madfis, 2009; Petee, Padgett, & York, 1997). These studies implicitly assume that there are no meaningful differences in the characteristics of those who perpetrate and the forces that shape these events. This is a questionable assumption at best. Research suggests perpetrators of mass publics not differ in their motivations, but also in the way they prepare, execute, and conclude their attack (Bowers, Holmes, & Rhom, 2009; Duwe, 2004, 2007).

Recognizing the implausibility of such assumptions, some researchers have treated mass public shootings as a unique phenomenon related to, yet qualitatively distinct from, other types of mass murders (Capellan, 2015; Kelly, 2012; Lankford, 2015; Obsborne & Capellan, 2015). Unfortunately, this is a recent effort, and our knowledge is limited to the incidence and the basic characteristics of the offenders and the event. As a result, much of what we think we know about mass public shootings has been inferred from the general literature on mass murders. Therefore, one cannot discuss mass public shootings without drawing from general literature on mass murders.

The existing literature on mass murders/mass public shootings revolves around four themes: definitional issues, prevalence, typologies, patterns, and risk factors. In the following pages, I focus on these themes to study literature on mass public shootings leading to mass murders.

2.1 Definitional Issues

Mass murder is a frequently misunderstood term. Holmes and Holmes (1992) noted that the term mass murder is often used interchangeably with serial and spree killing, despite key spatial and temporal aspects that separate these three forms of multiple homicides. Serial killers murder their victims over an extended period, often taking significant breaks in between victims. After murdering, the killers return to relatively functional adult roles (Delisi & Scherer, 2006; Fox & Levin, 2012). Spree killers murder their victims within a relatively short period, within hours or days, and they often commit murders in conjunction with other criminal activity. It is generally agreed that mass murder, unlike spree and serial murder, is the killing of a number of persons within 24 hours in one or more closely related locations (Aitken et al., 2008; Dietz 1986; Duwe 2004, 2005; Fox & Levin, 2003; Levin & Madfis, 2009; Palermo, 1997). While most mass murders occur at one location and at a specific time, this definition allows for events to extend over time and space for a 24-hour period. By extension, a mass public shooting has the same spatial and temporal aspects as a mass murder, but the perpetrator uses firearms to kill multiple victims in a public space.

Although the spatial and temporal aspects of the operationalization of mass murders is widely accepted in literature, there is less consensus on the number of dead victims that constitute a mass murder (Bowers, Holmes, & Rohm, 2010). While most literature settled on the three- to five-victim criterion (Aitken et al. 2008; Dietz, 1986; Duwe, 2004; Fox & Levin, 2012), some have opted for a two-victim criterion (Lankford, 2015; Levin & Madfis, 2009; Palermo, 1997).[1] Other researchers argued that the number of casualties is not only arbitrary but theoretically irrelevant to the study of the causes of mass murders. They argued that mass murder by intention (i.e., those who intended to kill as many people as possible but were unable to meet the two- to five-victim criterion) is also theoretically relevant and should be included in investigations on the etiology of this phenomenon (Aitken et al., 2008; Capellan, 2015; Mullen, 2009).[2]

The two-to five-victim criterion is problematic not only because it is theoretically irrelevant to the causes of mass homicide, but also because it has potentially biased the results of all studies on the subject. Current studies on mass murder are in effect studies of "successful" mass killers as defined by their respective victim criteria. These studies ignore random and systematic factors that may impact whether or not an offender *seeking* to become a mass murderer, actually becomes one. For instance, attacks excluded from the sample included those in which the perpetrator was a bad shot or had a low-caliber weapon. Attacks in which the wounded managed to escape or where the perpetrator was stopped by the police were also left out of the sample. In addition to these random factors, there may be systematic differences in the ways the police and Emergency Medical Technicians (EMTs) respond to these events, which would also affect the victim count. One could argue that the police and EMTs are better prepared and respond to these events faster and more efficiently today than 40 years ago. These systematic differences may affect the number of events that meet the victim criterion and subsequently bias

[1] These studies do not offer justification for the operationalization of mass murders.
[2] One unintended consequence of using different victim-count criteria is that it inhibits our ability to compare findings among studies. It is very difficult to determine whether new or contradictory findings among studies are because of real substantive differences or the operationalization of mass murders.

studies that do not include events where (despite the offender's intentions) the number of victims was insufficient for it to be classified as a mass murder.

2.2 Incidence of Mass Murder and Mass Public Shootings

One of the biggest misconceptions about mass murder is the notion that it is a new phenomenon in American life. Duwe (2005) noted that in the 1980s journalists and criminologists began to claim that the 1960s marked the beginning of an unprecedented wave of mass murders. Research on the prevalence of mass murders has shown that this notion is not entirely true (Duwe, 2000, 2004, 2005). Using a sample of 909 mass killings in the United States from 1900 to 1999, Duwe (2004) found that mass murders have been a relatively common occurrence in 20th century America. His analysis reveals two waves of mass murders during this period. The first wave took place during the 1920s and 1930s and consisted primarily (54%) of familicides. The average offender was a 40-year-old white (91%) male (92%), who committed the event in a private location (73%); he most likely used a firearm (53%), and committed suicide 48% of the time. Journalists were correct in saying that the mid-1960s marked the beginning of a mass murder wave, but it was not at all unprecedented. In reality, it marked the onset of the second wave of mass murders, which, according to Duwe (2004), continued into 1999. While the incidence rates of these two mass murder waves are quite similar, they are qualitatively different. Compared to the first, mass killers in the second wave were younger, less likely to be white (62%), less likely to be suicidal (25%), and more likely to use firearms (70%).[3]

[3] These differences are likely due to the rise of drug-related massacres. Drug-related massacres became commonplace in the 1970s because drug trafficking organizations started to grow and compete for the control of territory. The increase in felony-related massacres most likely exacerbated the differences in the characteristics between the two waves.

Using this database, Duwe (2004) commented on the most prevailing ideas about mass murders. For instance, it was believed that workplace massacres were a new strand of mass murders that emerged in the 1980s. However, Duwe (2004) showed that workplace massacres were nearly as common before the mid-1960s as they are today. Another prevailing belief was that mass murders had become more lethal in the last decades of the 20th century. Duwe showed that this was not borne out by facts. On average, mass murders were more lethal before the mid-1960s than later. Duwe did note, however, that the events had become more lethal in the 1990s. These results, however, may be outdated because some of the deadliest massacres occurred a decade after the research was completed.[4]

Duwe's (2004) study also revealed that the mid-1960s gave way to the rise of mass public shootings. It is important to note that mass public shootings are not a new type of mass murder. This phenomenon has taken place throughout American history, but not nearly at the rate seen after 1965. Between 1900 and 1965, 21 mass public shootings were reported by the media, amounting to a rate of 0.32 attacks per year. From 1965 to 1999, Duwe (2004) identified 116 mass public shootings, averaging 3.4 attacks per year, making mass public shootings the fastest growing type of mass murder in America. Subsequent research has shown that the incidence of mass public shootings has grown exponentially since the year 2000. Capellan (2015) reported 109 successful mass public shootings during 2000–2014, which translates to eight events per year.[5]

[4] There is also the issue of selection bias. Duwe (2004) relied on New York Times articles to identify mass murder events before 1960. His own analysis showed that the New York Times was significantly more likely to report events with more victims and in which high caliber weapons were used. It is likely that this bias led to significant differences in lethality for events pre- andpost-1960.

[5] By successful, I mean those perpetrators that killed 3 or more victims. I am using Duwey's (2004) definition to report consistent numbers.

In addition to the growing rate of incidence, several characteristics set mass public shootings apart from other forms of mass murders. The most obvious distinction is that mass public shootings are often directed toward unknown victims in public spaces. Most mass killings occur in private settings, with known victims, and are generally self-contained because they do not extend into the public space (Bowers, Holmes, & Rhom, 2009; Duwe, 2004, 2007). Mass public shooters are also unique in their desire to kill as many people as possible. This motivation shapes every aspect of the attack, which includes the planning and selection of targets and weapons. For instance, researchers have demonstrated that while guns were the weapon of choice for all mass murderers, mass public shooters were significantly more likely to employ high-caliber firearms (Duwe, 2004). Mass public shooters are generally suicidal or indifferent about their survival; they seem to be willing to die during the attack. In fact, a majority of mass public shooting events end in the death of the attacker either by self-contained suicide or suicide by cop. Another remarkable aspect this phenomenon is the degree to which these attacks have been perpetrated by teenagers within school premises. This trend is unique in two respects. First, teenagers generally do not commit mass murders. They are likely to engage in antisocial behavior, including homicide, but they do not usually commit mass murders. Second, while school shootings have taken place before 1996, none of the pre-1996 attacks were carried out by juveniles (Duwe, 2004). In the last 20 years, we have seen an unprecedented number of school shootings carried out by young men. These shootings, like all mass public shootings, have been dismissed as random.

2.3 Typologies of Mass Murders

A significant portion of literature has been devoted to the classification of mass murderers. The underlying assumption is that different subtypes of mass murderers have different patterns, explanations, and situational contexts. These are general typologies in that, ideally, they could be used to learn about any type of mass murder, including mass public shootings. While a number of typologies have been proposed, Dietz's (1986) typology is one of the first and most well-known. Based on the types of victims targeted, Dietz (1986) categorized mass murderers into three subtypes: family annihilators, pseudocommandos, and set-and-run killers. Family annihilators are those who murder their family members out of revenge, loyalty, or depression. Pseudocommandos possess a warrior mentality and meticulously plan their strategy and weaponry (Holmes & Holmes, 1992). They are often motivated by social and/or ideological issues; often the event is committed in the hope of drawing attention to themselves or to their cause. Set-and-run killers are often motivated by a sense of revenge toward specific individuals or places. Unlike most mass murders, set-and-run killers do not commit suicide; instead, they come prepared with an escape plan.

Holmes & Holmes (1992) added two more subtypes to Dietz's typology: "the disciple" and the "disgruntled employee." Disciple killers are often led by a charismatic leader. Their victims are strangers and their motivation rests outside the killer. In other words, it is the leader that demands action (Holmes & Holmes, 1992). Disgruntled employees are often former employees who have been "wronged" by coworkers or the employer. These individuals are generally fired or bullied. The shooter retaliates by going to their workplace and killing those "responsible" for his or her problem. This typology has received much criticism on several accounts. For instance, Petee et. al. (1997) argued that the typology proposed by Dietz (1986) and Holmes & Holmes (1992) is descriptive in nature; therefore, it is neither mutually exclusive nor exhaustive in the description of all possible mass murders. This consolidated typology is also based on small samples that are composed of the most sensationalized and atypical events.

Perhaps the most problematic feature of this typology is that it does not tell us anything beyond the suspect's characteristics. It aggregates the motivations, offender-victim relationships, and the execution methods.

Over time, researchers have stepped away from descriptive typologies and developed typologies based solely on the offender's motivations. Fox & Levin (2003) provided such a typology; they proposed three types that are expressive and two that are instrumental. This typology classifies mass murderers as revenge killers, power killers, loyalty killers, profit killers, and terror killers. Revenge killers are motivated by a grudge against a specific individual. Power killers are motivated by power and the need to dominate. Loyalty killers are motivated by a distorted sense of love and loyalty. Profit killers are motivated by a creed or a desire to eliminate witnesses. Terror killers are motivated by ideology and the need to convey a message.

Petee et. al. (1997) constructed a typology that included offender-victim relationships besides specific motivations. This typology classifies mass murders into the following nine subtypes:

(i) Anger/revenge: specific victim person(s)

(ii) Anger/revenge: specific place target

(iii) Anger/revenge: diffuse target

(iv) Domestic/romantic related

(v) Direct interpersonal conflict

(vi) Felony-related

(vii) Gang-motivated

(viii) Politically motivated mass murders

(ix) Nonspecific motive cases

Offenders in the *anger/revenge: specific victim person(s)* category seek revenge against a particular person(s). In the *anger/revenge: specific place target* category, offenders target a particular location that represents the source of strain. Persons in the *anger/revenge: diffuse target* category are fueled by anger and revenge; however, the offender does not have a direct relationship with the location. They target strangers in unknown locations. The offender might not be aware of the fact that sometimes the victims and location represent the source of strain. In the domestic/romantic category, the offender murders family members or a romantic interest along with other people. Direct interpersonal conflict arises immediately from a heated argument or some other type of interpersonal conflict. Felony-related mass murders are done in conjunction with any other criminal event, such as robbery. Gang-motivated mass murders are done in conjunction with gang activity. Politically motivated mass murders involve extremist ideology; this is usually done for some political cause. Nonspecific motive cases are those that cannot be easily classified; the motive is known only to the offender.

While the efforts to create informative typologies have helped, at times, it has also created some confusion. These typologies are not mutually exclusive, nor are they driven by a theoretical framework. Petee et. al. (1997) and Fox and Levin (2003) seemed more preoccupied with creating an exhaustive typology than a methodologically sound and theoretically useful one. Their emphasis on exhaustiveness has led to the over-classification of mass murder. A sound typology, like a sound theory, must be parsimonious. These typologies have failed in that regard.

In an attempt to avoid the aforementioned pitfalls and create a typology specific to mass public shootings, Osborne and Capellan (2015) developed a typology of mass public shooters (or active shooters) using a quasi-inductive approach guided by script analysis and rational choice theory (see Cornish, 1994). In their analysis, three scripts (or types) emerged: autogenic active shooter, victim-specific active shooter, and ideological active shooter; each type revolved around the motivation for the event. The autogenic active shooter events are "self-generated" because of the offender's internal psychological processes and issues (Mullen, 2004). These events often seemed motiveless because the offenders choose victims at random. However, the motive itself is to maximize the number of victims.

Victim-specific active shooter events involve offenders seeking revenge against one or several victims. These offenders tend to be driven by revenge; therefore, these shootings are generally caused by a precipitating event (e.g., divorce, unemployment, cheating, etc.). While the offender's goal is to kill one or two people, they often target unknown individuals after beginning their attack. Ideological active shooter events are motivated by political or racist ideologies. Similar to autogenic events, the underlying inner conflicts of killers are projected onto the victims who might be government officials or people from certain racial backgrounds.

Subsequent research on this typology reveals key differences between these types of mass shooters. Osborne and Capellan (2015) found that, contrary to popular perception, autogenic mass shootings (popularly known as deranged shooters) are not the rule, rather they are the exception. Victim-specific active shooter events constitute the most common type of mass shootings. They also found that autogenic active shooters are more likely to suffer from mental illnesses than victim-specific shooters. Capellan (2015) compared the ideological active mass shooters with non-ideological mass shooters. His analysis showed that while these individuals have remarkably similar demographic and personal profiles, ideological extremism has a significant influence on the way these offenders prepare, execute, and conclude their attacks. The results showed that ideological active mass shooters are more methodical than their non-ideological counterparts. They are significantly more likely to have a better strategy and use a greater number of firearms and additional (non-firearm) weapons, resulting in a significantly higher number of victims.

2.4 Patterns and Correlates: Identifying the Risk Factors of Mass Murders

While the typologies discussed above have been informative in some respects, they still do not offer explanations or insights into the factors that contribute to the incidence of mass public shootings specifically or mass murders in general. To fill this gap, a large portion of this research has been devoted to identifying recurring patterns in these attacks in the hope of isolating the individual-level risk factors for mass murders. For instance, researchers have found that mass killers are more likely than normal homicidal offenders to be older, white males (Delisi & Scherer, 2006; Fox & Levine, 1998). Their life histories are plagued with psychosis, paranoia, depression, and isolation (Bowers, Holmes, & Rhom, 2009). Often these individuals were bullied as children and because of their various mental illnesses they rarely establish themselves in effective working roles as adults (Mullen, 2004). Mass murderers tend not to accept personal responsibility for their long history of frustration and failure; they externalize blame and hold friends, family members, coworkers, or society accountable for their misfortunes (Fox & Levin, 1998). Mass killers often find themselves trapped in this vicious cycle of isolation, externalization of blame, and frustration. This cycle renders them particularly vulnerable to traumatic events, such as divorce and loss of employment. These acute events have been known to trigger attacks (Duwe, 2004). It has been established that mass murderers tend to be suicidal and many take their own lives during the course of the event (Holmes & Homes, 2001).

In addition to these individual characteristics, researchers have also identified some macro-level forces that may be associated with the incidence of mass murders. For instance, Duwe (2004, 2007) noted that the first wave of mass murders, which were primarily familicides, coincided with the agricultural depression and rise in divorce rates during the 1920s. The second wave of mass murders also overlapped with social upheaval, unprecedented drug use, and the unraveling of the U.S. economy, which characterized the 1960s. Interestingly, Duwe (2004, 2007) found that mass murder rates throughout the 20th century mirror those of homicides. The significant correlation ($r = 0.50$) between mass murders and homicide rates suggests that these two events may be the result of the same underlying processes. Duwe also noted that the association between the two forms of homicides weakened substantially after 1975; it decreased from 0.54 to 0.32.

Research on patterns, correlates, and risk factors of mass murders suffers from the same flaw as most of the research dedicated to typology building: they are not driven by theory. Thus, while the patterns and risk factors are known, there is a lack of convergence on the etiology of mass public shootings and mass murders. To the best of my knowledge, only Levin and Madfis (2009) have applied and integrated existing criminological theories to understand all the contributing factors. They integrated aspects of three different theories—strain, social control, and routine activities—into a five-stage sequential model of strain, which they called the cumulative strain model. In this model, they emphasized the interaction and buildup of multiple causal factors that were required for a mass murder to occur. Levin and Madfis explicitly assumed that these conditions are necessary, but they are not by themselves sufficient to trigger a massacre.

Levin & Madfis (2009) applied this multistage cumulative strain model to school massacres. The first stage of this model is *chronic strain*, which is characterized by prolonged periods of strain caused by a long string of failures and frustrations. Naturally, individuals who have a strong support network are better equipped to deal with chronic strain; however, those who do not have these prosocial bonds are marginalized and, consequently, lack external controls on antisocial behavior. Thus, the second stage of the process, *uncontrolled strain*, is characterized by feelings of marginalization and lack of conventional prosocial bonds (i.e., support structures). This, in turn, renders individuals vulnerable to life-changing events, which could lead to the third stage associated with such catastrophic losses: *acute strain*. Unable to cope with acute strain and feeling that they have nothing to lose, these individuals decide to get even. Then, they advance to the fourth stage or *planning phase,* where the mass killing is fantasized and acted upon if certain conditions are present (e.g., availability of firearms). The final stage is the *massacre* itself. This is where the individual takes revenge over those perceived to have "wronged" him. From a psychological perspective, this is the final power-asserting moment of an existence characterized by powerlessness.

While the cumulative strain theory of Levin and Madfis (2009) make a commendable effort to understand all the individual-level risk factors, it falls short in two important areas. First, the theory lacks nuance. Although the authors posit that this theory is specific to school massacres, the theory has been used as a general theory of mass murder. This could be because the authors themselves cite other types of mass killings to support their sequential model. However, even if judged as a general theory of mass murder, cumulative strain fails to explain, hypothesize, or even speculate why individuals who reach acute strain must enter the planning phase. Surely, there could be alternate outcomes. For instance, individuals who experience acute strain may decide to hurt themselves and commit suicide (inward violence). Other such individuals may unleash violence against others (outward violence), but not in the form of mass murders. In fact, mass murder is the least likely outcome in that sequential model, yet Levin and Madfis (2009) do not explain why their trajectory must lead to school massacres. Second, the cumulative strain theory is untestable. The theory requires detailed life-course information on individuals who have committed these massacres and those who have not. Individuals who engage in mass killings are loners and often commit suicide after the massacre; therefore, it is challenging to collect information about all the sources of strain and determine transition points between these stages. Given these difficulties, it is not surprising that the cumulative strain theory has never been tested.

2.5 Trapped by Dogma

Social scientists have given us important insights on the prevalence, types, individual risk factors, and patterns of mass murders. However, we still lack a fundamental understanding of the processes that shape the frequency and distribution of mass public shootings. Our failure to tap into these dynamics is rooted in our inability to escape the dominant paradigm in which this phenomenon has been examined. In the last 40 years, literature on mass murder has been restricted by an analytical framework that cares only for individual risk factors. Current literature on mass public shootings uses the same framework. This paradigm is myopic because it assumes that the proximate causes (i.e., factors and events closest to the attack) are the only ones that shape the frequency and distribution of these acts. As a result, literature has concentrated on identifying and accumulating such individual risk factors. Unfortunately, even after 40 years of individual-level research, we are not any closer to understanding the processes that lead to mass public shootings.

In 1974, John McKinlay, a medical sociologist, addressed the Medical Heart Association about the state of medical practice in the United States. To convey his frustrations adequately, he used the analogy of a fast-flowing river to represent illnesses and argued that doctors have been so preoccupied with saving individuals from drowning that they have ignored the reasons why individuals were being thrown in the water in the first place (Cypress, 2004). In other words, the emphasis on what he called “downstream” endeavors (i.e., short-term, individual-based analysis) was distracting doctors from the bigger dynamics going on “upstream.” In the same fashion, the dominant paradigm in which mass murder is examined preoccupies itself only with downstream thinking. The emphasis on individual-level pathologies has become a significant obstacle in the formulation of a theoretical understanding of these massacres because the social contexts in which mass public shootings occur are abstracted from empirical considerations.

To identify the determinants of mass public shootings, we may need to study the characteristics of populations, not individuals. It is a fallacy to infer that individual-level risk factors could be aggregated to understand the prevalence of mass public shootings in the population. Researchers must look upstream—away from the proximate causes for the mass public shootings and toward the distal causes that reside in societal structures.

CHAPTER 3
THE SOCIOLOGICAL IMAGINATION UNBOUND

3.1 Mass Public Shootings as a Social Fact

Knowingly (or unknowingly), in his analogy, McKinlay invoked ideas that Emile Durkheim had put forth 80 years back. In the late 19th century, Durkheim actively sought to carve out a unique domain for sociology: one that would highlight its distinctiveness from philosophy and empirical psychology and thereby validate its empirical imperative. Durkheim submitted that social phenomena should be understood as objective "social" facts that reside outside of individual consciousness. In other words, when individual actions combine, they give rise to a new collective consciousness different in nature from its individual units. Social facts include customs, norms, institutions, morality, populations, technology, and so forth. While social facts are the product of combined human activities, they are not the product of conscious intention. Rather, the sum of individual actions assumes its own life and thinks and acts only for its own survival—that is, social facts ensure that individuals accept, promulgate, and defend it.[6] Social facts interact with one another and affect people. However, while social facts are rooted in individual consciousness and actions, they cannot be understood at the individual level; they can only be understood in the network of interactions between the individual units—that is, in society.

There are four key propositions at the core of Durkheim's positivist stance. First, given that social facts are "things" external and independent of the individual actions that created them, it follows that social phenomena cannot be explained merely by individual factors. To

[6] Socialization and education are the key mediums for the transmission of social facts. Laws and associated punishments are the key ways by which social facts are defended from would-be violators.

understand the “way in which society conceives of itself and the world that surrounds it, it is the nature of society, not that of individuals that must be examined” (Durkheim, 2014, p.11). Second, social facts constrain individual behavior. All human behavior is carried out in social contexts that determine the parameters of acceptable conduct. Those who accept and follow the social norms go about their days unscathed by these coercive forces. However, those who do not accept or function within these parameters are made subject to shame and ridicule; they are marginalized and sanctions are imposed on them until they conform to their social contexts. Thus, the behavior that appears to emanate from individual consciousness is, in fact, shaped by the social context (i.e., ecology). Third, social facts can be identified by examining the means and rates of individual actions. Lastly, while not directly observable, social phenomena are things that should be studied empirically, not philosophically. “To treat social phenomena as things is to treat them as data, and this constitutes the starting point for science” (Durkheim, 2014, p.37).

Throughout his work, Durkheim successfully laid out a framework for identifying, theorizing, and systematically examining all social phenomena, including mass public shootings. Therefore, before engaging in upstream thinking, we must first reframe mass public shootings as a social phenomenon. To invoke Durkheim, rather than viewing mass public shootings as private events isolated from each other with each requiring separate examination, we need to consider that the whole may be greater than its individual parts. “[This]… collective total…is itself a new fact *sui generis*, with its own unity, individuality and consequently its own nature—a nature dominantly social” (Durkheim, 1979. P. 46). Recasting mass public shootings as a social phenomenon unshackles our sociological imaginations from downstream thinking and enables us to consider new alternative processes.

3.2 Mass Public Shootings: Homicide or Suicide?

> Every scientific investigation concerns a specific group of phenomena which are subsumed under the same definition. The sociologist's first step must therefore be to define the things he treats, so that we may know—he as well—exactly what his subject matter is. This is the prime and absolutely indispensable condition of any proof or verification. A theory can only be checked if we know how to recognize the facts for which it must account.
>
> (Emile Durkheim, 2013, p. 41)

Casting mass public shootings as a social fact is not sufficient although it may be a prerequisite for proper sociological examination. Before a valid theoretical treatment can be applied, we must first ascertain the nature of the phenomenon. In this case, mass public shootings have traditionally been classified and examined as an extreme form of murder. This is not surprising given that a multiple homicide is at the center of every event. However, there is another recurring aspect of mass public shootings, which has been largely ignored by the media and empirical research—most massacres end in suicides or in suicide by cop situations. The emphasis on homicide over suicide is understandable. The act of committing multiple homicides in a public space is a disturbing event, particularly when the victims are selected at random. However, we cannot ignore the high suicide rates. It is also important to recognize that these shooters may have lost the will to live long before they decided to reach for a firearm.

Research on the subject supports the idea that mass shooters are more likely than regular homicidal offenders and other types of mass murderers to commit suicide (Delisi & Scherer, 2006; Duwe, 2004). It may be this suicidal state (or indifference about their own lives) that allows them to commit these horrible attacks. As Costa (2013, p. 1) noted, "Once the individual loses the will to live…the most abhorrent atrocities become permissible. There are no longer any consequences to fear: no arrest, no jail, no trial, no families of the victims to face, no remorse." It is possible that the murder itself is committed to justify the murderer's own deaths. Menniger (1938) posited that those who commit suicide are not only consumed by hopelessness and guilt but also by a desire to punish themselves. Lankford's (2015) study supported this idea. His analysis of mass public shootings revealed that the odds of committing suicides increased by 20% for every additional victim. From this perspective, mass public shootings may be driven by a suicidal, not murderous state, and they should be seen as an extreme form of suicide—one that involves murder.

3.3 Murder or Suicide? Comparing and Contrasting Known Patterns

We cannot, however, frame mass public shootings as an extreme form of suicide or homicide based on conjecture alone. We must contrast the known patterns of mass public shootings to those of homicides and suicides to understand the true nature of this phenomenon. Let us start with homicide. Compared to mass public shooters, regular homicidal offenders seem to have a much stronger sense of self-preservation (Lankford, 2015). To avoid detection, typical homicidal offenders generally attack in private settings, away from public view (Brantingham & Brantingham, 1981). After the event, many engage in some form of precautionary act, such as crime-scene staging (Goberth, 1996; Hazelwood & Napier, 2004; Ferguson & Petherick, 2014; Turvey, 2000); others simply flee to avoid detection. Mass public shooters do not exhibit such behavior. Osborne and Capellan (2015) reviewed the crime scripts of all known mass public shootings from 2000 to 2012, and found that not a single mass shooter engaged in crime-scene staging. They also found that only a minority of offenders fled the crime scene (about 15%) and approximately 50% of offenders who fled were later arrested (because they surrendered) and the other half committed suicide after fleeing (see Osborne & Capellan, 2015). The difference in the sense of self-preservation is seen in the data: 62% of homicides were cleared by the police as compared to 100% of known mass public shootings. Approximately 40% of mass public shootings ended in suicides (excluding suicide by cop) compared to only 4% of homicides. Another key difference is that mass public shootings are, exclusively, an expressive form of violence—the attack is an expression of anger, frustration, and other negative emotions. A significant portion of regular homicides could be categorized as instrumental in nature because it is committed for profit or gain (see Block & Block, 1991).

Mass public shootings and regular homicides not only differ in their motivations and sense of preservation, but also in the profiles of the perpetrators. Mass public shooters are more likely to be white males much older than the typical homicidal offender (Capellan, 2015; Kelly, 2012). The gender and age differences are particularly noticeable. Approximately 96% of all mass shooters are male compared to 77% of regular homicidal offenders. Similarly, the age distribution for mass shooters and regular homicidal offenders varies substantially. The age distribution for regular homicidal offenders is unimodal. It begins to rise at the age of 14 and reaches its peak in the late 20s and early 30s; after this, it begins to drop exponentially. The age distribution for mass shooters is trimodal. It reaches its first peak in the age range of 15–19 years; then, it drops and remains stable throughout the 20s. It begins to rise again in the early 30s, reaching a second peak in the early 40s, followed by a final rise in the mid-50s (Kelly, 2012).

Suicide and mass public shootings share remarkable similarities. First, both phenomena involve individuals who have little regard for their own preservation. While this is obvious in suicide cases, in the absence of a formal diagnosis, a script analysis of mass public shooters shows that they do not behave in a manner consistent with someone trying to avoid authorities and/or escaping unscathed from the event (Osborne & Capellan, 2015). Second, similar to mass public shootings, suicide is exclusively an expressive form of violence directed inward toward the individual—there is no profit or gain in it; on the contrary, suicide represents the end of a life plagued with frustrations, psychosis, depression, and social marginalization. There are also similarities in the personal profiles of these perpetrators. Similar to mass shooters, those who commit suicide by using firearms tend to be white (92%) males (96%) in their early forties. This median age, however, hides the trimodal distribution that mirrors closely the distribution of mass public shooters (O'Brien & Stockard, 2006).

3.3.1 Drawing from Similar Literatures

Although compelling, the similarities between various forms of mass murders do not provide a definitive answer about the nature of mass public shootings. Unfortunately, drawing from similar literatures will not provide a satisfactory answer. For instance, studies in terrorism literature have not provided any conclusive answers to questions regarding suicide bombers (Townsend, 2007). Although it may seem strange to ask whether "suicide" terrorists are driven to their deaths by suicidal tendencies, research on the matter has revealed a mixed picture. Some argued that suicide terrorists are not suicidal at all but rather are driven by a range of motives such as *istishad* (martyrdom in the service of Allah), personal revenge, coercion/indoctrination, and/or rational strategic behavior (Hassan, 2001; Kushner, 1996; Pape, 2003). Other researchers, especially Lankford (2013, 2014b), claimed to have provided evidence that suicide terrorists are suicidal. A discussion on the merits of each argument would be outside the scope of this study; however, it would be fair to say that no camp has conclusively demonstrated whether these events are driven by a murderous or a suicidal intent—it is likely that there are a variety of motivations including suicidality.

Although they share some similarities, certain substantive differences prevent us from making similar inferences about the suicidal or the murderous natures of mass public shooters, on the one hand, and suicide bombers on the other hand. The first difference is that mass public shooters do not coordinate their efforts, whereas suicide bombers are radicalized, recruited, and prepared by terrorist organizations. Mass public shooters, even the ideological ones, act alone (Capellan, 2015). This self-selection process likely makes mass public shooters quite different from suicide bombers. Second, the mode of attack (i.e., a bomb) necessitates that suicide bombers kill themselves to successfully carry out the attack. Mass public shooters do not have this dilemma. All suicides committed by mass shooters in the United States are self-contained in that they do not hurt anybody else. Third, and most importantly, suicide bombing is a phenomenon that occurs exclusively outside of the United States. Religious, cultural, and situational factors shape the meaning and social construction of these attacks. Hence, a mass public shooting attack in the United States may not be equivalent to a suicide bombing in the Middle East and their motivations might be completely different.

Homicide followed by suicide of the perpetrator is a phenomenon more closely related to mass public shootings than suicide bombings. As the name denotes, murder-suicides involve individuals who have murdered and shortly thereafter (i.e., within 30 days) committed suicide (Haper & Voigt, 2007; Henry & Short, 1954). Etiologically, mass public shootings might be a subtype of murder-suicides because the former are generally followed by suicide. Researchers have struggled to classify the phenomenon of suicides in homicide-suicide literature and suicide bombing literature. Scholars have treated homicide-suicide either as a type of murder (Stack, 1997; Wallace, 1996) or as suicide (Marzuk & colleagues, 1992); some have chosen to cast homicide-suicides as a unique phenomenon—not just a murder or a suicide (Harper & Voigt, 2007). The emphasis of literature on descriptive and typological accounts has also hindered our theoretical understanding of the subject (Harper & Voigt, 2007).

Unfortunately, empirical literatures on suicide bombings and homicide-suicide do not provide any definitive answers to whether these attacks were driven by a murderous or a suicidal state. Clearly, this is a hard question to answer given the nature of the events. However, considering the similarities between suicides and mass public shootings (such as the disregard for self-survival), the possible role of suicidality cannot be entirely disregarded. Consequently, while suicide cannot be definitely proven to be the driving force behind mass public shootings, it cannot be definitively disregarded as a major motivating factor. A sociological examination of this phenomenon must account for the social processes that lead to both murder and suicide.

CHAPTER 4
APPLYING THEORIES OF SUICIDE AND HOMICIDE TO MASS PUBLIC SHOOTINGS

To a certain extent, mass public shootings embody characteristics of both homicide and suicide. For that reason, any sociological investigation of these massacres must account for the known causes of these phenomena. This is particularly important when, as in this case, there is no known precedent or investigation that can lead to correct theoretical approach. The murderous-suicidal characteristics of these massacres combined with a lack of direct literature demand that an "integrated" theoretical approach be used. By "integrated" it is meant that theoretical perspectives that have been successful in explaining suicide and homicide must be examined together in a single model. Because this study has no precedent, pulling various theories from the homicide and suicide literatures is necessary to begin to unravel the social causes of mass public shootings.

Furthermore, this integrated approach will allow us to better ascertain the nature of mass public shootings. In other words, it will allow us to discern whether mass public shootings as phenomenon behaves like homicide or suicide. If theories that have been used to explain homicide do a good at explaining the incidence of mass public shootings, and those used to explain suicide do not, then we would conclude that mass public public shootings behave more as a homicide since it is subject to the same forces that shape in the incidence and distribution of homicide. Conversely, if suicide theories do a better job than homicide theories, we would conclude that mass public shooting is closer to the phenomenon of suicide. These insights will provide a stepping stone for the future examination of these massacres.

For this reason, I employ three major theoretical perspectives in social sciences: Durkheim's theory of social integration, Shaw & McKay's (1942) social disorganization theory, and the theory of imitation/diffusion stemming from the works of Tarde.

4.1 Social Integration

In *Suicide*, Emily Durkheim offered an ecological explanation for what is an extremely personal act. From his perspective, suicide is an individual choice; however, it is a choice directly and deeply rooted in the group and social life of the individual. The causes of suicide reside at the social level. To provide evidence for this claim, Durkheim examined the spatial and temporal patterns for suicide rates in Europe. His analysis showed that the rate of suicide varied greatly between countries. Some countries, particularly Scandinavian, had a high "aptitude" for suicide. Aptitude is a measure of the proportion of suicides per total population. Others countries had very low incidence of suicide. This aptitude toward suicide seemed to be related to modernity and religious life. Data showed that suicide rates are positively associated with modernization. Protestant countries had a substantially higher suicide rate than Catholic countries. Despite the large variations between countries, suicide rates did not vary much over time within countries. Generally, societies with high suicide rates had similar rates of suicide over time and vice versa. Durkheim noted that substantive fluctuations in the rate of suicide within countries were associated with significant changes in structure of the economic, political, and social system.

In addition to country-level differences, Durkheim also examined suicide data for groups within societies. The analysis showed that men had higher suicide rates than women. Single persons, including widows and widowers, had higher suicide rates than those who were married. Individuals with higher levels of education had a higher incidence of suicide. These differences were robust across Europe. From these observations, Durkheim concluded that individual characteristics (i.e., psychological factors) could not account for the large variations in suicide rates that were seen (a) amongst countries, (b) within countries across time, and (c) amongst genders, religions, and other groups. Building on his earlier work on social order, Durkheim hypothesized that suicide is directly linked to the level of social cohesion in society. Specifically, he theorized that high suicide rates were an indicator of weak social cohesion (at least in modern societies).

The core of Durkheim's argument is that the degree of social cohesion among members of society is a function of two related forces: social integration and regulation. Social integration is the "intensity of the collective life circulating in it [i.e., in society]. It is more unified and powerful the more active and constant is the intercourse among its members" (Durkheim, 1951, p. 202). Accordingly, individuals who are integrated well into their communities are able to place the interest of the whole above their individual interests. Conversely, in weakly integrated groups, individuals depended less on one another. In this environment, individuals do not recognize any interests other than their own. Durkheim stated that "the individual ego asserts itself to excess in the face of the social ego" (p. 209). Hence, insufficient social integration creates individualism, which leads to suicide and other antisocial behavior. The second social cause of suicide is social regulation. Durkheim contends that persons, on their own, are incapable of inhibiting their innate and unquenchable desires. Left to themselves, individuals are bound to pursue goals that are unattainable, leaving them in a perpetual state of unhappiness. According to Durkheim, the collective consciousness must moderate the desires of the individual to achieve equilibrium. A well-regulated society "fixes with relative precision the maximum degree of ease of living to which each social class may legitimately aspire….Under this pressure, each in his sphere vaguely realizes the extreme limit set to his ambitions and aspires to nothing beyond. At least if he respects regulations and is docile to the collective authority" (Durkheim, 1951, p. 249). The unregulated state leads to suffering, which in turn leads to a myriad of social pathologies, including suicide.

Durkheim postulated that varying levels of social integration and regulation lead to four different types of suicides: egoistic, anomic, fatalistic, and altruistic. Insufficient social integration leads to egoistic suicide. According to Durkheim, egoism explains the differing suicide rates between religious groups; it also explains why unmarried and childless adults are more at risk of suicide. However, excessive social integration will also lead to suicide—one that is altruistic in nature. Altruistic suicide occurs when individuals are so well integrated into society that their own lives become insignificant relative to the group's needs. For instance, in medieval Japan, vassals were known to engage in *junshi* ("suicide through fidelity") upon the death of their master. Weak levels of social regulation lead to anomic suicide. This often happens when the norms and values are disrupted by rapid social change leading to uncertainly about accepted behavior. According to Durkheim, anomic suicide is prevalent during times of economic depression and regime change. Conversely, excessive levels of social regulation lead to fatalistic suicide. Fatalistic suicide occurs when an oppressive discipline or political regime pitilessly blocks the passions and the abilities of individuals to control their present and future. Egoistic and anomic suicides are only present in modern societies, which are increasingly characterized by a divergence of individual interests and collective needs. Altruistic and fatalistic suicides are more likely to occur in traditional societies where individuals are highly integrated and are regulated by the collective.

While Durkheim's theory of social integration and regulation has become the dominant perspective in the study of suicide for over a century, it has not emerged unscathed from criticism. *Suicide* has been critiqued on a number of accounts, such as its analytical rigor (Robinson, 1950; Pope, 1976), data employed (Atkinson, 1978; Day, 1987; Poppel & Day, 1996), macro-micro level mechanisms (Gibbs, 1968), and definitional issues (Berk, 2006). All these are legitimate arguments worthy of empirical examination and discussion; however, one argument is particularly relevant to this study. I refer to the theoretical distinction between social integration and regulation. As originally laid out, integration and regulation are two distinct forces, but several scholars rejected this distinction and argued that regulation and integration are part of the same dimension (Johnson, 1965; Pope, 1975; Mainon & Kuhl, 2008). Individuals cannot be well regulated unless they are well integrated into society. Likewise, individuals cannot be well integrated into society, unless they are well regulated by it. Durkheim himself acknowledged that the state of egoism (low integration) and anomie (low regulation) are "merely two different aspects of the same social state" (Durkheim, 1951, p. 288).[7] If integration and regulation are part of the same construct, then egoistic and anomic suicides are fundamentally the same as fatalistic and altruistic suicides. Johnson (1965) and Pope (1976) argued that in the Durkheimian perspective, low social integration can be the only cause for suicide because fatalistic/altruistic suicides can only occur in traditional societies. If this interpretation is correct, then controlling one force accounts for the other. Compared to social regulation, the social integration thesis has been forged by over 100 years of theoretical refinement and empirical testing. Given this fact, I place social integration as the core of the Durkheimian perspective, in line with recent literature (Gibbs, 2000; Stockard & O'Brien, 2002; Maimon & Khul, 2008).

[7] Even those who argue that there is a difference between social integration and regulation do not agree on what that difference is, nor have they presented a way to test these differences empirically (Denelis & Pope, 1979).

4.1.1 Empirical Support for Social Integration

In the discussion of social integration, Durkheim posited that suicide rates vary inversely with the degree of integration of religious society, domestic society, and community life. Durkheim argued that religion provides protection from suicide because it promotes social interaction and shared values, and consequently forms strong social bonds. The integrative effect of religion is not homogenous. As Durkheim noted, certain religious denominations are more effective than others in integrating and thereby inhibiting antisocial behavior (Regnerus, 2003). For instance, Protestantism has historically had a looser grip than Catholicism on the collective life of congregations; therefore, Protestantism had limited ability to restrain antisocial behavior (Pescosolido & Georgianna, 1989). Durkheim's original analysis showed that, as hypothesized, suicide rates for Protestants were higher than that of Catholics. Empirical literature, however, has found only partial support for Catholic-Protestant differences (see Stack, 2000a). These disparities may be due to differences on how religious integration is conceptualized and operationalized.

A substantial amount of research has moved beyond Durkheim's denominational proposition into the causal mechanisms by which religion and certain theological traditions protect against suicide. This research resulted in two theoretical novelties. First, the protective effect of religion is not only a function of intensity, but it is also the core belief system of religious theology (Stack, 1983, 1996), specifically, how religious denominations treat misbehavior (Curry, 1996; Regnerus, 2003). Religious denominations that view morality categorically (most notably conservative Protestants) and accordingly treat misbehavior more seriously are more effective in controlling deviant behavior. Research on suicide and deviant behaviors have consistently shown that measures of Protestant conservatism are more predictive of suicide than the usual measure of total church adherence (Curry, 1996; Mainmon & Kuhl, 2008; Regnerus, 2003). The second theoretical innovation came from the religious network theory literature, which showed that the protective effect of religion intensifies in areas that enjoy high levels of denominational homogeneity (Breault, 1986; Burr & McCall, 1997; Pescolito & Georgianna, 1989; Pescolito, 1990).

Religious integration not only protects against suicide, but it has long been associated with reduced criminal activity (Bainbridge, 1989). Following the Durkheimian tradition, Hirschi & Stark (1969) argued that religious beliefs promote conformity in three ways: (1) religion gives legitimacy to values of the collective, (2) religious values are instilled through repetitive rituals, (3) religious values are enforced in life with the certainty of eternal reward or punishment after death. These religious values, which gave rise to what came to be known as the hellfire thesis and the moral community thesis, have received considerable support in literature. A meta-analysis conducted by Baeir and Wright (2001) showed that religious beliefs and behaviors have a moderating effect on criminal activity.

Family integration is a key component of Durkheim's social organization thesis. In fact, he discussed the importance of family integration more than any other aspect of social life (Danigelis & Pope, 1979). Durkheim postulated that low levels of familial integration would lead to the relative isolation of the individual from the integrative and regulative forces found in familial structures. Hence, single, widowed, and divorced persons are malintegrated because of the lack or loss of responsibility to their kin. Married persons with children are more integrated than married persons without children. Therefore, the size and intensity of domestic life inhibits suicide and other antisocial behaviors by the subordination of the individual's ego to the collective needs of the family. Despite different operationalizations, time periods, and units for analysis, empirical literature has supported the fact that family integration provides a protective influence over suicide (Breault & Barkey, 1982; Breault, 1986; Danigelis & Pope, 1979; Stack, 1980; Wasserman, 1984).

Similar to religion, family integration has been linked to a number of health and social problems (Goldman, 1993; Sampson & Laub, 1992; Sampson, Laub &Wimer, 2006; Porter & Purser, 2010). According to the CDC (2014) report, married persons are less likely to smoke, drink heavily, and be physically inactive. Consequently, married adults are healthier than their counterparts. Marriage has also been consistently associated with reduced criminal activity. Research in life-course criminology has shown that many of life's transitions (such as becoming a parent or getting a job) help in crime desistance. When individuals experience these conventional turning points, the tendency to engage in crime diminishes because of the added responsibilities. Marriage has been shown to be a significant event, capable of rerouting criminal trajectory in a more conventional direction (Sampson & Laub, 1992; Sampson, Laub &Wimer, 2006). Community-level marriage structure, usually measured as percent divorced, has been linked with increased levels of violence and property crimes (Porter & Purser, 2010; Wilcox & colleagues, 2005; Wooldredge & Thistlewaite, 2003).

4.2 Social Disorganization Theory

In more ways than one, Shaw & McKay's (1942) social disorganization theory is the criminological version of Durkheim's social integration theory. Similar to Durkheim in *Suicide*, Shaw & McKay (1942) argued that criminal behavior is rooted in social-economic structure of communities, rather than individual traits. Social disorganization is not the first criminological theory to make the causal link between neighborhood characteristics and delinquency. In the early 1920s, Robert E. Park and Ernest W. Burgess sought to understand the uneven spatial variation of crime across communities. Looking at the spatial patterns of crime in the city of Chicago, Park & Burgess (1925) observed delinquent behavior was consistently greater in neighborhoods near or in what they called the “zone of transition.” The zone of transition is the part of the city designated for industrial manufacturing and house low-income residents. Importantly, Park & Burgess (1925) noted that these neighborhoods were plagued with high rates of crime despite complete turnover in their populations. Therefore, the characteristics of residents, whether be Italians, Polish, or Black, did not have an effect on crime rates. Hence, the causes of criminal behavior must reside in the social-economic structure of these communities.

Shaw & McKay’s (1942) contributed to Park & Burgess (1925) observations by identifying which and how structural characteristics of neighborhoods lead to crime. In its original elaboration, Shaw & McKay’s (1942) posit that the erosion of community-level organization or “social disorganization” were attributed to three neighborhood characteristics: (1) low *socio-economic status,* (2) high rates of *residential instability,* (3) and high-rates of *racial heterogeneity*. The link between these structural characteristics and elevated rates of crime and delinquency in urban communities are one of the most ubiquitous findings of criminology. Studies as far back as 19th century (Du Bois, 1899), to the most recent tests of the theory (Butcher et al., 2015; Morgan & Jasinski, 2016), and studies in between (Bursik & Grasmick, 1993; Sampson and Groves, 1989; Sampson & Bean, 2006; Silver, 2000; Weitzer, 2000) have consistently provided support for this link.

It is important to note that Shaw & McKay (1942) did not posit that a direct relationship between these social-economic structures and crime. Rather, they argued that certain socio-economic conditions in the community have the potential to breaks down the cohesiveness of the collective, weakening its ability to instill and enforce consensus on its norms, values, and goals.

In turn, this breakdown in collective efficacy or social capital gives rise to increased levels of crime and delinquency. Low *social-economic status* (SES) is hypothesized to be associated with higher crime rates through its effect on the community organizational base. Neighborhoods with low SES are characterized with low organizational participation, which is associated with weaker relational ties and unwillingness to intervene on behalf of the common good. Therefore, the effect of SES on crime operates through the erosion of formal and informal control. *Residential instability* was hypothesized to disrupt social relations within the community. The constant influx of new residents impede the establishment of meaningful pro-social bonds and consequently the creation and maintenance of dense friendship networks. The erosion these friendship networks, kinship bonds, and associational ties are said to lower guardianship, which in turns leads to crime. High *racial heterogeneity* is hypothesized to inhibit the ability of residents to share norms and create consensus due to racial, cultural, and language differences.

4.2.1 Developments and Empirical Tests

Since its classic elaboration by Shaw and McKay (1942), social disorganization theory has undergone rigorous critiques, tests and extensions. Sampson and Groves (1989) paved the way with the most groundbreaking test and extension of the theory. Previous to their 1989 study, researchers had only tested social disorganization theory indirectly. That is, they had only tested the direct effects of social structural factors—*social economic status*, *ethnic heterogeneity* and *residential mobility*—on crime. However, in the original elaboration, Shaw and McKay (1942) hypothesized that the effect of these social structural factors on crime would be mediated via their production of community social disorganization and weakened informal social control. Sampson and Grove (1989) were the first to test the causal mechanisms through which each social structural factor impacts the level of social disorganization and thereby crime.

Sampson and Grove (1989) also extended the classic conceptualization of social disorganization by adding *family disruption* and *urbanization* to the model. They claimed that *family disruption* decreased informal social controls at the community level. *Urbanization* is also expected to weaken local kinship and friendship networks and decrease participation in local affairs. Sampson and Grove (1989) found that much of the effect of SES, *ethnic heterogeneity, residential mobility, family disruption* and *urbanization* on crime and delinquency is mediated through the mechanisms mentioned above.

Subsequent extensions of social disorganization have been built on two distinct but similar theories: social capital theory and collective efficacy. Social Capital is defined by Putnam (1995) as the ability of community members to create connections that facilitate coordination and cooperation for mutual benefit—that is the transmission of resources via social ties. A key limitation with social capital is that these networks are a necessary, but not sufficient condition for social control (Kubrin and Weitzer, 2003). Having the ability to pull resources together for the common good does not mean it will occur—community members need to be willing to act. Sampson (2010) created the concept of collective efficacy to capture such willingness. Collective efficacy, built on social capita theory, is defined as the process of activating social ties among community members to achieve collective goals, such as public order (Sampson, 2010). Thus, social capital has to do with trust and solidarity, while collective efficacy has to do with the belief that community members can effectively control anti-social behavior. While both have received support in the literature, collective efficacy appears be the most powerful predictor of crime and delinquency of the two constructs.

Some argue that the tests and extensions discussed above only reveal part of the picture. According to Skogan (1990) traditional tests of social disorganization have all implicitly assumed that effect of low social control flows in one direction only—towards higher crime rates. In other words, these tests do not account for feedback mechanisms in which crime itself has an effect on the community social-economic structure. Under the recursive model of social disorganization, crime increases the fear of crime, which in turn decrease levels of community cohesion, organizational and increase residential mobility. The recursive mode of social disorganization has received support in the literature (Bellair, 2000; Steenbeek, & Hipp, 2011).

4.3 Mass Public Shootings, Social Integration, and Social Disorganization

Social integration and social disorganization theories embody different sides of the same coin. Both theoretical perspectives claim antisocial behavior (whether be suicide or homicide) is rooted in the community's inability to effectively integrate and regulate the individual ego. Both perspectives are concerned with the effects of modernity (in the case of Durkheim) and urbanization (in the case of Shaw & McKay) on the social cohesion of communities. Therefore, regardless of whether mass public shootings are conceptualized as murder, suicide or both, the social integration and social disorganization perspectives provide a great ecological framework for which to study the incidence of these attacks.

There is considerable evidence that the social cohesion that Americans enjoyed in first two-thirds of the 20th century has slowly, but steadily, been disintegrating. In *Bowling Alone*, Robert Putnam (2000) masterfully describes the decay process of the "social capital" in the United States. Putnam describes social capital as "the features of social organization such as networks, norms, and social trust that facilitate coordination and cooperation for mutual benefit" (2000, p. 66). Thus, it is a term used to describe the collective benefits derived from social networks, such as information flow, norms of reciprocity, collective action, and solidarity. His analysis showed that engagement in civil life has declined in areas such as religious services, organizational membership, volunteering, club meetings, and face-to-face interactions in friendship and family networks. This trend is largely explained by changes associated with the restructuring of the economy and modernity, such as the changing nature of the workplace, media, and suburban sprawls. However, the most important factor seemed to be cohort differences. According to Putman, the mature and silent (pre-WWII) generation was much more engaged in civil society than the baby boomers and subsequent generations.

The process of modernization and urbanization in America has eroded the ties of the individual to society. It is possible that the spatial clustering of mass public shootings coincides with spaces characterized by low social capita or social regulation and integration—that is, spaces that are socially disorganized. Although this is merely a hypothesis, it is very clear that the unraveling of civil engagement coincided with the rise of mass public shootings in the late 1960s.

4.4 Imitation: The Diffusion of Mass Pubic Shootings

The main alternative to ecological explanations like social integration and social disorganization perspectives is the theory of imitation stemming from the works of Gabriel Tarde. Tarde (1903) noted that suicide, like all social phenomena, could be caused by imitation of behavior, which along with innovation constitutes the basis of all social interactions. Thus, we learn from people, groups, and institutions in which we are anchored, particularly from significant others and those in proximity. According to this perspective, suicide is an idea similar to divorce, fashion, and abortion. Therefore, suicide can be communicated and learned, particularly by those who for one reason or another are predisposed to it. Suicide imitation suggests that suicidality can spread through the very ties that Durkheim theorized were protective (Abrutyn & Muller, 2014).

While Tarde posited a general theory of imitation for the study of all social phenomena, it was never formally applied to suicide until David Phillips did so 71 years later. The seminal work of Phillips (1974) examined the "Werther effect" to describe imitative suicide behavior. This name comes from the novel *The Sorrows of Young Werther* written by Johann Von Goethe. In the novel, a young artist who is in love with a married woman concludes that his suffering would end only when someone in the love triangle died. Unable to kill anyone, young Werther decides to kill himself. The novel was widely read in Europe, and it was believed that many who read it imitated the manner in which the protagonist committed suicide. Although it was never corroborated empirically, the novel was banned by governments throughout Europe. Believing that the Werther effect was no coincidence, Phillips (1974) set out to test for suicide contagion by looking at associations between printed news reports on suicide and national suicide rates from 1950 to 1970. His analysis showed that the national level of suicide increased significantly after stories are publicized by newspapers. Phillips' (1974) findings corroborated three key elements of his causal argument. First, he found that the number of suicides increased *after* the suicide stories were published. Second, higher levels of publicity led to greater increases in the national number of suicides. Lastly, spikes in suicides occurred primarily in areas where news stories were publicized.

Phillips' (1974) findings revived academic interest in suicide imitation via mass communication. The studies that followed have provided substantial support for suicide imitation. For instance, studies that have reexamined the influence of print media reports on suicide and suicide trends have corroborated Phillips' (1974) findings (Wasserman, 1983; Stack, 1992; Phillip et al. 1992; Ganzeboom & Haan, 1982; Kopping et al., 1989; Kesseler, 1988; Yoshida et al.,1991). Along with the original results, these studies reported that the influence was stronger (i.e., imitation was more likely to occur) when suicide stories are explicit, repeated, posted on the front page with large headlines, contained pictures, and involved celebrities. A similar association has been established between television news and the incidence of suicide. For instance, Bollen & Phillips (1982) replicated Phillips' (1974) study by using television news stories. Similar to the original article, they found a significant association between news stories and spikes in suicide cases. Their findings also suggested that the media's influence is temporary, lasting for on average of 10 days. The suggestive influence of suicide stories, however, is not limited to real life stories. Research has found a link between fictional suicide stories on television and surges in the incidence of suicide (Baron & Resiss, 1985; Ostroff et al., 1985; Ostroff & Boyd, 1987; Scgmidtke & Hafner, 1988).

The power of suggestion or imitation is not only limited to inward violence like suicide, but it also extends to aggressive behavior directed outwards. For instance, the study by Berkowitz and Macaulay (1971) reported increased levels of violent crimes following the assassination of President Kennedy in 1963 and the mass murder by Charles Whitman in 1966. Phillips (1983) also found highly publicized championship prizefights were followed by significant surges in homicides three to four days after the event. Zumar (1982) also found that bomb threats against nuclear plants spiked when stories of previous bomb threats were publicized by the media. A key policy implication of imitative violence thesis is that if media exposure to violence increases violent behavior, then reporting on punishments for such crimes should deter such criminals. Phillips and Hansley (1984) set out to test this hypothesis by performing a time series analysis of homicide rates. They found that media stories on murder trials and sentences deterred murderers for several days.

While much of this body of literature has been rightly criticized for numerous methodological pitfalls (see Baron & Reiss, 1985; Wasserman, 1984), the sheer volume of evidence in support of suicide suggestion and imitative violence cannot be ignored. Etzerdorfer and Sonneck (1998) acknowledged the difficulties inherent in using observational data to detect the effect of the media. They conducted a field experiment using media reports of suicides in the Viennese subway system. Vienna established its subway system in 1978, and shortly thereafter numerous instances of suicides were reported. Working on the assumption that suicide imitation is real and partly driven by media communication, Etzerdorfer and Sonneck's (1998) reduced the "dosage" of the treatment by having media organizations curtail or avoid reporting these events. The results were astonishing. As soon as media reports on subway suicides were decreased, there was a dramatic decrease in subway suicides. Within two years of the treatment, the incidence of subway suicides dropped by 80%, and in subsequent years, the incidence stabilized to a moderate level.

4.4.1 How do Ideas Spread?

To understand the process behind suicide imitation, we must abandon the vague language given by Tarde (1903) and adopt more precise concepts and framework for the diffusion of innovations literature. In his seminal work, *Diffusion of Innovations,* Rogers (2003) builds on the works of Gabriel Tarde and others to specify the general principles underlying the process of propogation of ideas within a social system. Diffusion of innovations refers to the spread of abstract ideas, technical information, public policy, cultural practices, and technology within a social system. The spread or diffusion denotes the flow of spatial or temporal movement from innovators to early and other potential adopters via communication and influence (Rogers, 2003). The communication of ideas and influence of prior adopters increases the probability of adapting the innovation. Thus, the diffusion of innovations theory aims to explain the dynamics of social construction and the gradual assimilation of new ideas among the members of a community over time (Roman, 2003).

The diffusion of ideas has four elements. The process first starts with the innovation itself. An innovation is an idea, practice, or object that is perceived (by individuals) to be new (Rogers, 2013). Given that these innovations exist, communication must take place for the innovation to spread within and between social groups. Rogers (2013) defines communication as the process by which adopters create and share information with one another to reach an understanding. In other words, adopters (i.e., individuals, organizations, schools, states, and countries) share basic information about the innovation; sometimes this includes opinions and experiences. In the context of diffusion of innovations, mass media channels represent the most efficient way to spread the existence of an innovation to potential adopters. Despite the broad reach of the mass media, individual networks tend to exert more influence on potential adopters (Rogers & Singhal, 1996). The third element in the diffusion process is time. The passage of time is necessary for the diffusion of innovations because innovations cannot be instantaneously adopted. By obtaining a better understanding of the rate of adoption and the changing characteristics of adopters, it may be possible to unlock the dynamics behind the diffusion process. Lastly, the diffusion of all innovations takes place within a social system. The diffusion process itself is subject to the cultural, political, economic, and social structures of the system. These structures can facilitate or inhibit the diffusion of innovations.

A fundamental assumption in most of the diffusion of innovations literature is that the adoption of an innovation is primarily a learning process. In the context of diffusion, this learning process has been modeled using the Social Learning Theory (Bandura, 1976). The central idea is that individuals are not born with performed repertoires of behaviors. At birth, the human mind is a "blank slate," and behaviors are learned through observational modeling. In other words, individuals observe a behavior and then do something similar. Observational modeling, unlike blind mimicry, allows for the learner to adapt or reinvent the observed behavior. Under the social learning theory, associations formed by conditioning, reinforcement, and punishment do not account for all learning. According to Bendura (1976), people can learn new information and behaviors by observing others in person or via the mass media. Of course, individuals are more influenced when the behavior they observe comes from individuals within their interpersonal networks. Unlike purely psychological approaches to learning, the social learning theory, like the diffusion of innovations framework, recognizes external or "social" forces (primarily the communication with other individuals) as the main driver for behavioral change.

4.4.2 Mass Public Shootings: The Imitation of Violence

The incidence of mass public shootings may be driven by a diffusion mechanism. That is, the occurrence of one event may increase the likelihood that other attacks will take place either in space or time. Anecdotal accounts lend support to this idea. For instance, the 1966 "high tower shooting" at University of Texas at Austin has been credited with prompting a string of mass murders, including the mass public shooting at Rose-Mar College in Arizona. Robert Smith, who perpetrated the attack, claimed he was inspired by the shooting in Texas, and that his goal was to make a "reputation" for himself by killing more people than Whitman (Duwe, 2005). In 1991, Thomas McIlvane killed five people in a Michigan post office after being fired for insubordination. Prior to the attack, McIlvane commented on a previous postal shooting in Edmond, Oklahoma. According to witnesses, he claimed he was going to make the shooting in

“Edmond look like Disneyland.” In addition to these incidents, at least a dozen attempted and completed mass shootings have a direct connection to the Columbine High School massacre, including the Virginia Tech shooting in 2007. Unfortunately, the cases where imitation clearly played a role are limited because most perpetrators died during the attack; therefore, information on the possible influence of previous mass public shootings was lost.

Despite the lack of information, the diffusion mechanism remains a viable explanation for the incidence of mass public shootings in two important respects. First, mass public shootings are highly clustered in space and time (Capellan, 2015). Spatial and/or temporal “clustering” is not a sufficient but a necessary condition for the diffusion of ideas. The type of clustering observed is a function of the communication channels. If the channels of communication are local, then the spread of adoption should cluster in space. However, if the communication channels are wide and far-reaching (e.g., mass media), then the spread of adopters should cluster in time. Second, as theorized under the diffusion of innovations literature and the social learning theory, innovations and behaviors cannot spread unless they are communicated to other potential adopters. Mass public shootings certainly meet this criterion because most of these attacks are surrounded by media frenzy. These incidents are covered by news organizations continuously for hours, and sometimes days. Perhaps most disturbingly, news accounts report the personal information of the attacker and the manner in which he or she planned, executed, and concluded the attack. These reports provide all the elements needed for imitation.

CHAPTER 5
AIMS AND HYPOTHESES

Durkheim's theory of social integration, Shaw & Mckay's (1942) social disorganization theory, and imitation/diffusion theory provide a great theoretical framework from which to commence a sociological investigation of mass public shootings. Historically, the social integration perspective and the imitation theory have been treated as opposing explanations to social phenomena. In this paper, I argue that not only can the opposing ontological assumptions be resolved (see Rafanell, 2009), but a valid test of one theory cannot be done without accounting for the other. This argument is based on two reason, one is theoretical and the other methodological.

Theoretically, the social integration and social disorganization are ecological theories. As such they make the "closed polity" assumption (Bugaug, 2008). Both theories assume that the incidence of mass public shootings (or any other phenomenon) is only a function of the characteristics *inside* the jurisdiction of the political boundary, whether it be states or counties. This assumption is questionable at best. The literature on diffusion has unequivocally shown that ideas, behaviors, and technologies diffuse through space and time (Rogers, 2013). Hence, behaviors in a social group may be influenced by the behaviors of neighboring communities. Methodologically, if social integration and social disorganization theirs are tested without controlling for possible local processes (e.g., imitation/diffusion) that induce spatial heterogeneity, the resulting spatial dependence will lead to biased parameter estimates (Anselin, 1988). Likewise, one cannot properly test for an imitation/diffusion process if the model does not account for the possibility that mass public shooting converge in space *because* the conditions that lead to suicide also converge in space. For these reasons, the primary aim of this study is to integrate these two different frameworks (i.e. ecological and imitation/diffusion) to explain the incidence of mass public shootings.

5.1. Hypotheses

The theories of social integration, social disorganization, and imitation/diffusion generate multiple observable implications for the analysis of mass public shootings. Based on Durkheim's theory of social integration, it is expected that communities with lower levels of religious, familial, integration will be at a higher risk of experiencing a mass public shooting attack. Similarly, based to social disorganization theory, it is expected that states with higher levels of disorganization will be at higher risk of experiencing a mass public shooting attack. It will be interesting to see if populations with low levels of social integration are the same as those that have high levels of social disorganization. Based on the diffusion/imitation theory, the occurrence of a mass public shooting is expected to increase the odds of future mass public shootings occurring around neighboring areas (spatial diffusion) and also across the United States (temporal diffusion). This is an important distinction because the diffusion mechanism may be spatial or temporal depending on the types of channels through which the innovation is being communicated.

In line with similar studies on imitation, I assume that information on mass public shootings is being communicated by the media. In essence, media coverage moderates the strength of the imitation effects. Under the imitation/diffusion perspective, those massacres that receive more media coverage are expected a stronger influence on potential attackers and vice versa. This assumption can be tested will be tested indirectly in this study.

In this study, I will test the following hypotheses:[8]

H1: The risk of experiencing a mass public shooting attack will be positively associated with low levels of *religious integration*.

H2: The risk of experiencing a mass public shooting attack will be positively associated with low levels of *familial integration*.

H3: The risk of experiencing a mass public shooting attack will be positively associated with higher levels of *social-economic status*.

H4: The risk of experiencing a mass public shooting attack will be positively associated with higher levels of *residential mobility*.

H5: The risk of experiencing a mass public shooting attack will be positively associated with higher levels of *racial heterogeneity*.

H6: The occurrence of a mass public shooting will increase the risk of future attacks in the surrounding area (*spatial diffusion*).

H7: The occurrence of a mass public shooting will increase the risk of future attacks for contiguous United States (*temporal diffusion*).

H8: Higher media exposure will increase the risk of future mass public shooting attacks.

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[8] Hypotheses are stated in terms of risk because event history models will be employed to test them. In event history models, the dependent variable is failure time, which translates into the hazard rate (or rate at which events occur). The results in these models are in the form of hazard ratios, which are interpreted as a decrease or an increase in the risk of failure. Hazard rations can also be interpreted as odds, probabilities, and median failure times. However, risk is a more appropriate interpretation of hazard ratios.

CHAPTER 6
DATA AND METHODS

6.1 Defining Mass Public Shootings

Before a full discussion of the methods, it is important to formally operationalize mass public shootings. A mass public shooting involves one or more individuals who are actively engaged in killing or attempting to kill multiple victims or as many victims as possible in a public space. This study concerns the causes for mass public shootings; therefore, it does not have a victim criterion. As discussed earlier, systematic and random factors that are independent from the intent of the shooter may affect the victim count and whether or not the perpetrator is classified as a mass murderer. This study steps away from the victim criterion by including shooters who clearly intended to kill many people but did not meet any established victim criterion. Four more elements are added to this definition:

1. It may involve more than one individual at multiple locations.
2. It may include instances where the violence spills to other unintended victims.
3. The perpetrator must use at least one firearm, but he/she is not limited to firearms only (Other implements, such as knives, bats, and explosives could also be used).
4. The shooting is not related to other profit-driven criminal activity (e.g., drug trafficking, or gang shootings).

6.2 Data on Mass Public Shootings

Research on mass murder has traditionally relied on official crime statistics for information on the incidence and characteristics of mass killings (Duwe, 2007; Fox & Levin, 2012; Levin & Fox, 1985). This is for good reason. Official data sources, such as the FBI's Supplementary Homicide Report (SHR), provide some incident-level information on all known homicides in the United States. These reports include information on the location, race, and gender of offenders and victims; it also provides information on victim-offender relationships, weapons used, and circumstances of the crime (Fox, 2004). For a long time, the SHR was the only feasible way for researchers to identify and gather basic incident-level data on mass murders in the United States.

The advantages of SHR have in certain cases outweighed its limitations. Primarily, the SHR is well known for its missing data problem. The SHR does not report on all known homicides and also lacks information for reported ones (Fox, 2004; Fox & Swatt, 2009; Pizarro & Zeoli, 2013). This missing data problem is most likely because of non-random mechanisms that make multiple imputation techniques and valid inferences a daunting task. The information reported by SHR has also been found to have some degree of inaccuracy (Pizarro & Zeoli, 2013). This is particularly the case with factors such as the circumstances of the homicide (Loftin, 1986; Maxfield, 1989), victim characteristics (Braga, Piehl, and Kennedy, 1999), and victim-offender relationships (Fox, 2004). Research shows that this problem is exacerbated when data is reported in the initial stages of investigation and involves homicides with multiple victims (Huff-Corzine et al., 2014). In addition, the SHR does not report on homicides prior to 1976 when the first SHR was published; it also lacks specificity on the type of locations and circumstances of the homicide, making it difficult for researchers to disaggregate mass murders into theoretically relevant subtypes.

Given these limitations, it not surprising that researchers have turned to open-source data to identify and collect incident-level information on mass murders and mass public shootings (Blair, Nichols, Burns, & Curnutt, 2013; Capellan, 2015; Kelly, 2012; Duwe, 2004, 2005, 2007; Lankford, 2010, 2015; Osborne & Capellan, 2015; Petee, Pagett, & York, 1997). Open-source data is information that is open to the public (Chermak, Freilich, Parkin, & Lynch, 2012). This data often comes in the shape of searchable electronic documents (e.g., newspaper articles and government documents) that can be accessed via the Internet. While susceptible to the same sources of error, open-source data offers several advantages over official sources of data. First, open-source data can be used to identify and collect information on incidents prior to 1976. For instance, Duwe (2007) used open-source data to identify mass murders that happened as far back as 1900. Perhaps the primary advantage of open-source materials is the availability of more information than official sources. Media reports and government documents include the names of offenders and victims, their motives, criminal histories, preparation, execution, and conclusion of homicides. Thus, open-source data enables researchers to reconstruct mass murders (and other types of events) in detail; this would not have been possible using official data alone.

For these reasons, this study relies on open-source materials to identify and collect information on mass public shootings. For attacks that occurred between 1960 and 2014, the mass public shooter database is compiled from government reports, previous scholarship, and media reports. The primary source, however, was the Kelly's (2012) active shooter report. The report identified 324 events that occurred between 1960 and 2012, including foiled attempts. Using the criteria discussed above, 225 cases were identified. This initial list was cross-referenced with additional mass public shooting lists provided by peer-review journals, new organizations, school-sponsored reports, blogs, and online encyclopedias (see Table A1, Appendix A for a complete list of sources). The cross-referencing process led to the identification of 70 additional shootings.

After the final list of active shooter events was generated, eight online search-engines were used to obtain detailed information on the offenders, victims, and incidents (see Table 1).

Open-source materials, such as media accounts, legal documents, blogs, videos, and government documents, were used to piece together the available information. From this information, I prepared the most complete picture possible of the offence including information about the offender's motivation, the location of each event, the victim information, and the manner in which the offense was carried out and concluded (see Table A2 for a complete list of variables in the dataset). While all available sources were used to construct the database, it is important to note that over 90% of all information came from news sources.

Table 1. Web Search Engines Used for Data Collection

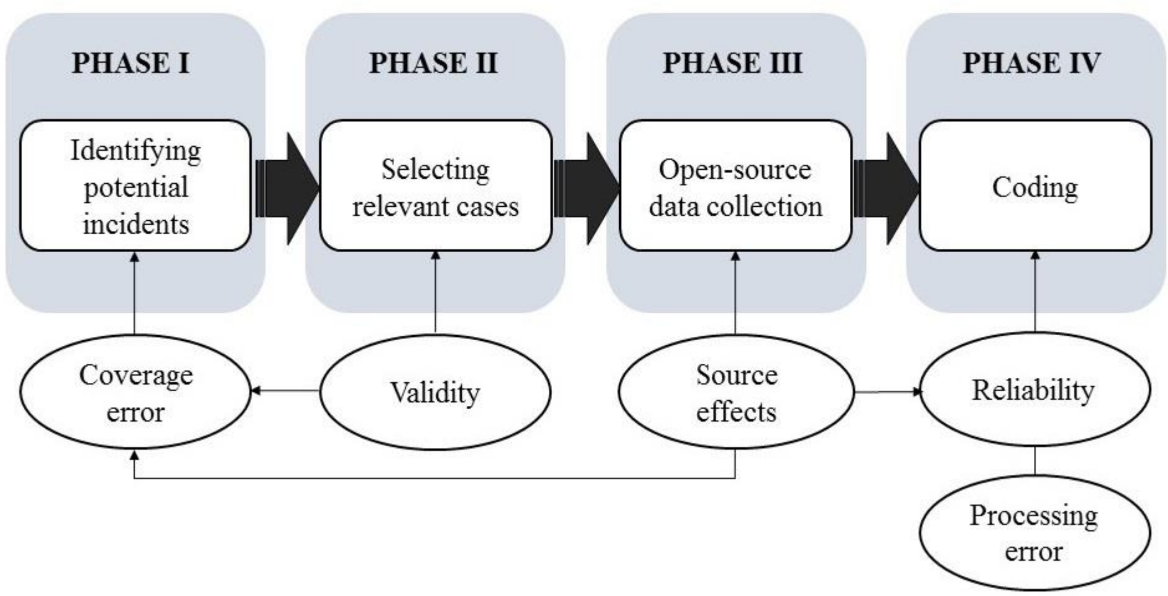
1. Lexis-Nexis	2. Proquest
3. Yahoo	4. Google
5. Copernic	6. News Library
7. Westlaw	8. Google Scholar

6.2.1 Sources of Error

All data collection strategies, whether they involve surveys, administrative records, or open-source data, are susceptible to error. This study is no exception. While error cannot be avoided completely, it can be minimized by understanding and reducing the possible sources of bias that creep into every stage of the data collection process. Figure 1 describes the data collection process along with the potential sources of bias.

I started the data collection process by constructing a list of multiple homicides that may fit the definition of a mass public shooting. The goal in this stage was to identify the universe of cases; that is, every mass public shooting (as defined above) that took place in the United States from 1960 to 2014. This stage of the process is susceptible to coverage error. In survey methods, a coverage error occurs when there is *undercoverage* i.e., some members of the target population are excluded from the sampling frame. In open-source data methods, undercoverage occurs when cases are systematically excluded from examination because they were never identified. While various mechanisms could induce such biases, two are particularly relevant to this study: *publicity effects* and *time-period effects*. Publicity effects is a phenomenon whereby events that are more "attractive" receive more news coverage and consequently are more likely to be identified than other less attractive events. Literature on the media coverage of crime has consistently shown that crimes that involve unknown and young victims and had higher number of casualties get longer and more in-depth news coverage than less egregious crimes (see Chermak, 1997; Duwe, 2007). Thus, we can expect that mass public shootings that do not possess these characteristics are less likely to be identified and included in the analysis. *Time period effects* refer to the sampling bias in favor of recent incidents. In other words, because of the Internet and mass media, mass public shootings are more likely to be identified today than 20 years ago. Similarly, the further back one goes in time, the greater is the sampling error, especially if the events that occurred in the past are not particularly egregious.

Figure 1. Data Collection Process and Possible Sources of Bias



While it is impossible to know the extent of undercoverage, there are ways to reduce this type of bias. Primarily, I relied on a cross-referencing process to uncover potential mass public shooting events. After obtaining the primary list, it was crossed-referenced with more than 50 additional lists of potential mass public shootings. These lists were provided by a wide variety of sources, including peer-reviewed journal articles, books, government agencies, news organizations, and blogs. Through this cross-referencing process, additional mass public shootings were uncovered. While I cannot guarantee that all mass public shootings from 1960 to 2014 were identified, this dataset is closer to the universe of cases than any other database available today.

After all potential mass public shootings were identified, the second step is to apply the criteria set forth in this study to select the appropriate cases. Validity is key at this stage. Validity refers to how accurately a measure or, in this case, a potential event fits with the conceptualized definition. Including invalid cases (i.e., events that are not mass public shootings) in the analysis will lead to a coverage error called *overcoverage*, that is, the inclusion of events that are not part of the target population. In this study, a mass public shooting is defined as an event in which one or more individuals actively engage in killing or attempting to kill multiple people in a public space. At the core of this definition is the intent of the offenders to kill at least multiple victims and, at most, kill as many people as possible. Given that a large portion of offenders die during the attack, it is impossible to know their intent. However, this study relies on the observable implications of the attack itself to collect evidence for or against this key criterion. These observable implications include factors such as the number of shots fired, people targeted, people dead, and weapons used. Besides these, prior statements, confessions, and witness accounts are used to estimate the intent of the offender. These factors together minimize the chances of including an attack that does not meet the conceptualized definition.

Once all mass public shootings have been identified, the next step was to collect materials on the incident. Materials included demographic characteristics of offenders and victims and information about the planning, execution, and resolution of the each mass public shooting. To collect these materials, open-source materials were accessed using a variety of online search-engines. It is important to acknowledge that the type and quality of information collected may be affected by the type of the source from which it originates. This phenomenon, which is referred here as *source effects*, may profoundly influence the accuracy and comprehensiveness of the information collected. For instance, some sources may focus on the more sensationalistic aspects of the shooting (e.g., methods used, guns, victims, etc.), and not on other equally important factors (e.g., life history, mental illness, etc.). Some sources may provide more accurate information than others. In such a scenario, relying on one source of information affects not only the quality but also the type of information obtained. To reduce this source of bias, this study used a wide variety of information sources (e.g., news coverage, police reports, court documents, academic work, blogs, etc.) and different online search engines.

The final step in the process involved recording all the information in a manner that is consistent and useful for analysis. This process is known as *coding*; it is a process prone to two dangerous sources of bias: reliability and processing error. In the data coding process, reliability is the dependability or consistency of the information obtained. In this stage, reliability issues come in the shape of conflicting accounts of the same event. For instance, Kelly (2012) found this problem with the information obtained on weapons. In my own coding, I have encountered this problem with the "number of dead/injured," the "number of weapons," and the "types of weapons" used. The coding protocol minimizes this source of error in three ways. First, given that news accounts appearing immediately after the event give more erroneous information (see Kelly, 2010; Huff-Corzine, 2014), more weight was given to news stories published some weeks after the event had occurred. Second, more weight was given to more reputable sources of information, such as government and court documents (over news accounts) and news reports (over blogs). Finally, the information in the question is triangulated with different types of sources before it is coded.

The coding process is also subject to processing error. Processing error is a human error that causes the recorded information to be incorrect. These errors may be due to unclear coding protocol, fatigue, difficult-to-use coding platforms, and typos. Several steps were taken to tackle these potential sources of processing error. First, a clear coding protocol was developed to minimize confusion in the operationalization of variables and its values. Second, to avoid coding fatigue, coding sessions were conducted in four-hour windows. Third, instead of coding directly into the Excel spreadsheets, Google forms were used to develop a clear easy-to-use coding platform. Finally, after data was uploaded into an Excel form, it was visually inspected to detect more obvious errors.

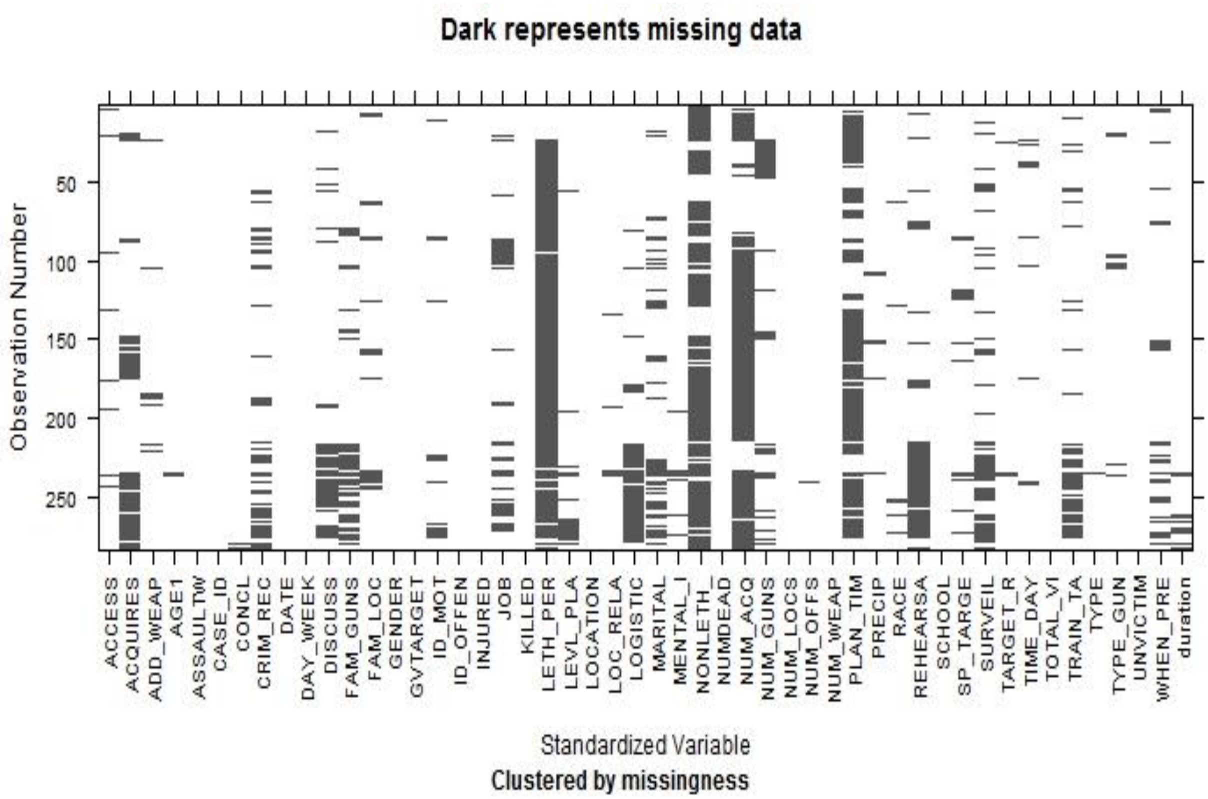
6.2.2 Missing Data

In addition to the sources of error discussed above, missing data can also inhibit our ability to make valid inferences about mass public shootings. Specifically, missing data and the way we deal with missing data often results in biases, efficiency losses, and incorrect standard errors (McKnight, McKnight, Sidany, & Figueredo, 2007). These problems are exacerbated if the missing data mechanisms are not random or completely random.[9] While missing data can

[9] Data are Missing Completely At Random (MCAR) when the probability of missing data on a variable *X* is unrelated to other measured variables, unobserved variables, and the values of *X* itself. In other words, the missing data can

rarely be completely avoided, its problems can be minimized if the extent of missingness is explored, the possible data mechanisms are hypothesized, and the appropriate resolution techniques are employed. Figure 2 presents the missing data patterns in the Mass Public Shooting database. Clearly, there are many variations to the extent of missing data. Some variables do not have any missing information, others have extensive missing data. There is no missing data in the variables included in this analysis (i.e., date, location, number dead, school shooting, unknown victims, government target, and assault weapons).

Figure 2. Missing Data Patterns in Mass Public Shooting Database



be thought of as random sample of the complete dataset. A more realistic scenario is data that is Missing At Random (MAR). Data are MAR if the missing data is related to other observed data, but not to the values of X itself. These missing data mechanisms are said to be "ignorable." A missing data mechanism that cannot be ignored is Missing Not At Random (MNAR). Data is said to be MNAR when the missing observations are related to the values of unobserved data.

The other source of data for this study comes from the United States Decennial Census for the years 1970, 1980, 1990, 2000, and 2010; as well as the American Community Survey (ASC) for the years 2011, 2012, and 2013. The census is conducted once every ten years; therefore, data will be missing in the years between decennial censuses. These missing values will be estimated using linear interpolation between decennial censuses. Linear extrapolation will be used to estimate the missing values for the year 2014.

6.3 Analytic Strategy

This sociological investigation of mass public shootings will begins with Exploratory Spatial Data analysis (ESDA) (Anselin, 1998). ESDA is a collection of techniques used to visualize and describe spatial distributions (De Smith, Goodchild, & Longley, 2007). ESDA generally begins with a visual inspection of the data. The goal at this stage is to identify possible spatial regimes or clusters. The visual tools employed depend on the type of variable. Typically, variables that take on a Gaussian distribution are represented in choropleth maps. However, if the variable of interest is a "pure point process," like mass public shootings, then visualization techniques, such as Kernel Density or "heat" maps, will be employed. Kernel density estimation visualizes points with respect to their concentration. The estimated density of events at regular grid points is a function of nearby observed events. The general formula for any point *x* is

$$\frac{1}{nh}\sum_{i=1}^{n} k\left(\frac{x - x_i}{h}\right),$$

where x_i re the observed points for $i = 1 \ldots n$ locations in the study area, $k(.)$ is the kernel function that assigns decreasing weight to observed points as they approach the bandwidth *h*. Points that lie beyond the bandwidth *h* are given zero weight.

After likely clusters are identified, significance tests examine whether these clusters are unlikely to have arisen by chance alone—i.e. statistically significant. For pure point processes, Ripley's K function is the preferred method. The K function summarizes spatial dependence or autocorrelation over a range of distances. In other words, it allows the researcher to determine if the phenomenon is dispersed, clustered, or randomly distributed over a range of distances. This test takes the following form:

$$L(d) = \sqrt{\frac{A \sum_{i=1}^{n} \sum_{j \neq i}^{n} k(i,j)}{\pi n(n-1)}},$$

where d is a fixed distance, n is the total number of points, A is the total area containing the points $k(i, j) = 1$ if the distance between the points i and j is less than d, and equal zero otherwise.

This function counts the number of neighboring mass public shootings within a specific distance range. This count is compared to the number of events one would expect to see under Complete Spatial Randomness (CSR). If the number of mass public shootings over a given distance is higher than the expected count under CSR, then the distribution is significantly clustered. If this count is smaller the the distribution is significantly dispersed. However, if the k function is within the 95% confidence interval of the CSR count, the the distribution is said to be random.

Ripley's K function is a very useful global measure of spatial autocorrelation. However, as as a global or omnibus measure of spatial autocorrelation, it only tell us that significant spatial autocorrelation exists, but not where it exists. SatScan's spatial scan statistics solves this problem by locating significant high-risk and low-risk clusters over a given space. The space scan statistic is defined by a moving cylindrical window with a circular geographic base. This method finds the clusters that maximize the likelihood function based on a Poisson distribution; these potential clusters are then tested for significance using 999 Monte Carlo replications (Recuenco et al., 2007). For the Poisson distribution, the likelihood ratio statistics is proportional to

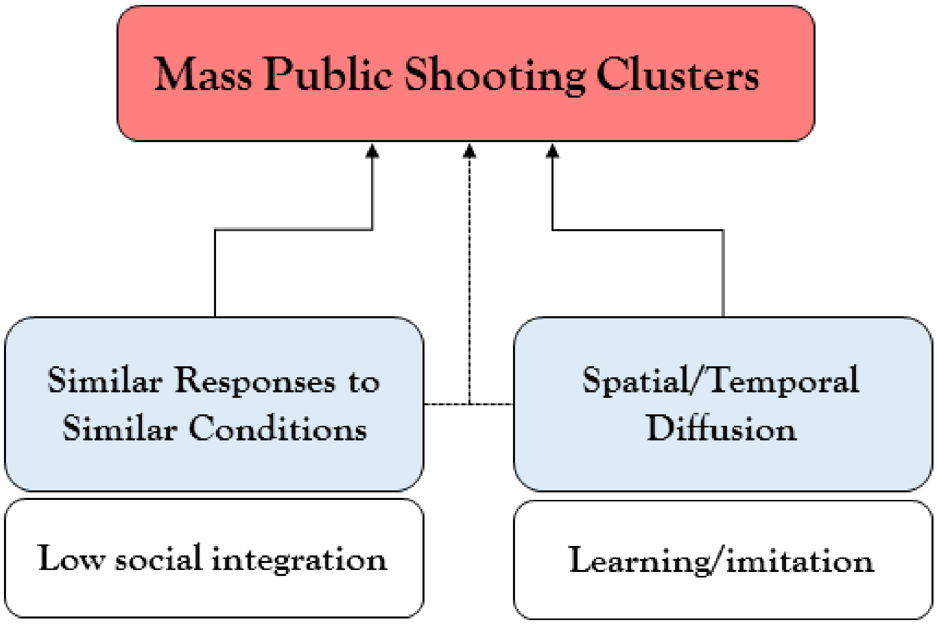
$$\left(\frac{c}{E[c]}\right)^{c}\left(\frac{C-c}{C-E[c]}\right)^{C-c},$$

where C is the total number of cases, c is the number of cases within the zone, and $E[c]$ is the expected number of cases under the null hypothesis that the case rate within the zone equals the rate outside the zone. SatScan also offers similar tests for detecting significant temporal clusters as well as spatial-temporal clusters.

The set of techniques under ESDA is particularly important for this study because significant spatial and temporal clustering provide evidence supporting the idea of underlying social causes. A social phenomenon that is only a function of individual attributes and decisions, do not cluster in space and time once population size have been accounted. If it does, it suggests that individual attributes and decisions are not only the cause. The clustering of social phenomena suggests that population-level or social factors also play a role.

According to Elkins & Simmons (2004) there are at least three possible explanations for the spatial and/or temporal clustering of social phenomena. One explanation explanation is that individuals respond similarly, but independently, to a similar set of circumstances. In our case, mass public shootings significantly cluster in space and/or time because the factors that lead to their incidence also cluster in space and/or time. These factors are called *ecological determinants*. In this study, social integration and social disorganization theory represent two ecological determinants or explanations for the clustering of mass public shooting attacks.

Figure 3. Possible Social Explanations for the Clustering of Mass Public Shootings



A second possible explanation is an interdependent, but uncoordinated, decision-making process. This explanation implies that individuals are uncoordinated in making the decision to engage in a mass public shooting, but they are interdependent because they factor each other's choices (see Elkins & Simmons, 2004). This explanation makes the case for an imitation or diffusion process. As discussed in section 4.3.1, ideas and behaviors may diffuse spatially or temporally. Spatial diffusion is known as *neighborhood effects*, whereas temporal diffusion is known as *hierarchical effects* (Berry & Berry, 1990). A third possibility is that both processes (diffusion and internal determinants) explain clustering in mass public shootings. In this case, both mechanisms would significantly and independently contribute to the incidence of mass public shootings.

Unfortunately, no descriptive technique can discern which process/es is responsible for the incidence and distribution of mass public shootings. To that end, multivariate statistics.

6.4 Modeling Strategy

This study will model the incidence of mass public shootings for contiguous U.S. states from 1970 to 2014 using a continuous time Event History Analysis (EHA) framework (also known as *survival* or *hazard* models). The goal of EHA is to explain the occurrence of an event at a particular moment. In regression, we usually study how factors are associated with the presence or absence of an event (e.g., death, heart attack, recidivism, etc.). In an EHA framework, however, we study how factors affect *the time to* an event, also known as *failure time*. While this difference may be subtle, the EHA framework provides significant advantages over logistic regression because of the following factors:

(1) EHA models account for censuring.

(2) EHA models allow for the comparison of median/mean event times for different groups.

(3) EHA models can explicitly model social processes.

(4) EHA models allow for time-varying parameters—that is, the effects of covariates may vary over time. These four advantages highlight the fact that time is at the core of EHA; this makes EHA a more nuanced and dynamic analysis.

The variable to be explained in EHA models is the time to an event also known as the *hazard rate*. The hazard rate is defined as

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t \leq T \leq t + \Delta t | T \geq t, x)}{\Delta t},$$

where T denotes a nonnegative continuous random variable for the time to an event, and t denotes the time (i.e., years, age, etc.). The hazard rate gives the rate at which units fail by t, given that the units have survived until t (Box-Steffensmeier & Jones, 2004). For instance, a hazard rate of four per day means that if this rate were to continue for an entire day, we would expect four failure times (or events). The above definition also implies that the hazard rate is conditional on a set of random independent variables (*x*). Assuming that all individuals share identical hazard functions, we can express the hazard rate as a product of two components:

$$h_i(t, \mathrm{x}) = h_0(t) \exp(\beta' \mathrm{x}),$$

where $h_0(t)$ is the baseline hazard function, and $\beta'\mathrm{x}$ is a vector of regression parameters. This representation is known as the Cox proportional hazards model. This is the most popular EHA model because it provides several advantages over parametric models— primarily, that the shape of the hazard does not need to be specified and time-varying covariates are allowed.

The Cox PH Model presented above assumes that each subject can only experience one event. However, in many situations, subjects may experience repeated or multiple events. Repeated events bring another layer of complexity because repeated events create subject-event dependence and heterogeneity (see Box-Steffensmeir et al., 2007). In the case of subject-event dependence, when a subject experiences repeated events, the timing of these event failures is likely correlated within the subject. In other words, experience of the event will influence experience of future events. In the case of heterogeneity, some subjects are more likely to experience the event for some unobservable factors. Subject-event dependence and heterogeneity creates within-subject correlations when the time to event failures violate the independence assumption of traditional EHA (Jones & Branton, 2005). Literature provides several solutions to these problems. The first is called the counting process model. Assuming that the events are independent, the counting process model fixes the problem by adding a new start time for the subject *i* in every failure time. However, there are occasions when it is safe to assume within-subject correlations. In these situations, a widely use technique for adjusting the correlations among recurring events is *robust estimation*. This technique adjusts the estimated variances of regression coefficients for a fitted model to account for misspecifications of the structured correlation (Zenger & Liang, 1986). Mass public shootings are recurring events; therefore, they are treated like the counting process model. To further ensure unbiased estimations, robust estimation is employed to adjust for possible within-subject correlation.

6.4.1. Unit and Time-Period of Analysis

The units of analysis for this study are states in mainland United States. While the unit of analysis is to be selected purely on theoretical grounds, methodological constraints make this difficult. Given the rare nature of mass public shootings and the continuous-time EHA model, treating state boundaries as the unit of analysis was the ideal compromise between adequate resolution and sample size to detect significant effects. For instance, the analysis from 1970 to 2014 translated into 805,376 state-days for 295 mass public shootings. If we employ a smaller unit of analysis (such as counties) then, during the same period, we would have 5,930,265 county-days for 295 incidents. Clearly, higher levels of resolution reduce our ability to detect significant events. Treating states as units provides a good compromise between resolution and power (directly linked to sample size) to detect any significant effects.[10] Non-contiguous states and territories of the United States were not included in the analysis. This criterion excludes Alaska, Hawaii, and other offshore U.S. territories. The logic behind this criterion is that tests of diffusion require units of analysis to have neighbors. Alaska and Hawaii do not share borders with any other U.S. territory and thus cannot be included in the analysis.[11]

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[10] The selection of a unit of analysis may bias results because of what is known as the modifiable areal unit problem (MAUP). This problem arises due to the imposition of artificial boundaries on a spatial phenomenon. Changing the artificial boundary, changes the values of the outcome and predictor variables and inevitably the results themselves (Heywood, 1988). Given that mass public shootings have never been subject to the examination proposed here, it is not possible to know whether mass public shootings are best studied with higher resolution boundaries, or whether it is a phenomenon that can be captured through a state-level examination. It is possible that mass public shootings are a regional phenomenon.

[11] Specifically, the computation of spatial matrixes can fail if the dataset contains islands and other borderless polygons. For this reason, one often sees diffusion tests for mainland United States.

6.5 The Model

As noted above, the dependent variable in this study is the time to a mass public shooting attack, with the "clock" resetting itself after each event failure (i.e., attack). The covariates used to explain these failure times fall into three categories: diffusion effects, exposure, and internal determinants.

6.5.1 Independent Variables

Diffusion effects. As noted earlier, this study will control two types of diffusion mechanisms: *neighborhood effects* and *hierarchical effects*. The underlying assumption here is that the risk of experiencing a mass public shooting for the state *i* will be directly influenced by the presence or absence of mass public shooting events in other states. This risk is presumed to increase if other states have experienced an event and to decrease if they have not. In case of neighborhood effects, the strength of the effect is assumed to be bigger if the event occurred closer in space to the state *i*. Conversely, for hierarchical effects, the influence will be stronger and closer in time.

To gauge neighborhood and hierarchical effects, this study employs a series of spatial lags. Spatially lagged variables capture spatial dependence by lagging the value of the dependent variable one unit in space to capture the behavior of neighbors (Etkins & Guzman, 2008). In other words, the spatial lags reflect the influence of unit *i* on its neighbors. There are two dimensions to the spatial lag (Wy^*). W is an M by N by T spatial weights matrix of values; it contains information on the "neighborhood" structure for each location. The second component is y^*, which is an N by T matrix of values that presents the values of y for neighboring states. In this case, y^* represents the number of mass public shootings experienced by the neighboring states during a given period. Using these two components, weighted averages of y^* are computed by dividing the sum of its products with *W* by a row sum of *W*. This calculation takes the following form:

$$\frac{w_{ij} + w_{ik}y*_k + \ldots + w_{in}y*_n}{w_{ij} + w_{ik} + \ldots + w_{in}}$$

The most important element of the weight matrix is determining the neighborhood structure. The neighborhood structure (i.e., who is a neighbor to the state *i*) are determined in two general ways: distance-based, and spatial continuity-based weights. Spatial weights are a function of geographic distance. Distance-based weights assign a higher weight (or influence) to polygons (states in this case) that are closer in space and less to states farther away. Some popular distance-based weights include: inverse distance, fixed-distance, and *K* nearest neighbors (see De Smith, Goodchild, & Longley, 2007).

While distance-based weights are popular in the natural sciences, it is not often used in the social sciences. In the social world, whether or a community is considered a neighbor has less to do with distance and more with borders, which leads to the second general way of conceptualizing the neighborhood structure: spatial contiguity or adjacency. Under spatial contiguity only polygons that share a border (i.e. adjacency) with state *i* are considered neighbors. Adjacency is popularly conceptualized through queen-based contiguity. Under queen contiguity neighbors must share either a line or a vertex (see the first order queen contiguity in Figure 4). Polygons that share borders, as defined by queen, are given a weight of 1 (adjacent), else they are given a value of 0 (nonadjacent).

Figure 4. First and Second Order Queen Spatial Contiguity

Queen (First Order)

0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	1	1	1	0	0
0	0	1	*i*	1	0	0
0	0	1	1	1	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0

Queen (Second Order)

0	0	0	0	0	0	0
0	0.5	0.5	0.5	0.5	0.5	0
0	0.5	1	1	1	0.5	0
0	0.5	1	*i*	1	0.5	0
0	0.5	1	1	1	0.5	0
0	0.5	0.5	0.5	0.5	0.5	0
0	0	0	0	0	0	0

As defined above, queen continuity is refered as "first order" continuty because only those polygons that share a physical border with polygon *i* are considered contiguious. First order contiguity weights are often inflexible and unrealistic measures of neighorhood structures because there are many instances where polygons that should be considered neighbors are not simply because they do not share a physical border to polygon *i.* Second order queen spatial weights fix this problem by assigning a weight of 0.5 to polygons that do not share a border (line and/or vertex) but do with polygon *i*'s first order neighbors. It is important to note, that it is impossible to determine which neighborhood structure is appropriate for the spatial process at hand. These different structures must be tested before being employed in a multivariate model.

Another element of a spatial lag is time. Spatial lags must be lagged in time also to establish causal order. In other words, only mass public shootings that occur in the past can affect likelihood of future mass public shootings occurring in the future. This assumption excludes the possibility of contemporaneous effects. Similar to neighborhood structure, it is impossible to know which time lag is appropriate before they are tested.

As noted above, spatial lags make key assumptions about the process in which information and learning travel geographically (i.e. neighboring structure) and the time taken for the causal effect to run its course (i.e. time). It is impossible to know these components *a priori.* For that reason, I will test a series of first and second order queen-based spatial lags that are lagged 6 months, one year, three years, and five years into the past. This series of lags will not ensure that the most appropriate measurement is used, but also allow to test for the robustness of any significant findings.

Media exposure. Research on suicide imitation has consistently shown that suicides that get more coverage in the news are significantly associated with larger spikes in incidents of suicides (Wasserman, 1983; Stack, 1992; Phillip et al., 1992; Ganzeboom & Haan, 1982; Kopping et al., 1989; Kesseler, 1988; Yoshida et al., 1991). This media exposure in essence moderates the strength of the neighborhood and the hierarchical effects. The mass public shooting attack that receives more exposure or news coverage has a stronger influence on potential attackers and vice versa. There are two ways to model this exposure. Ideally, exposure effects are captured by studying the different newspaper articles, TV news reports, and the types of news organizations that reported on the attack (i.e., national vs. local). Unfortunately, this was not feasible because of time constraints and the increasing bias we found for reports from the 1960s. For incidents that occurred many decades back, it is difficult to obtain a true measure of the number of articles published on the event. Hence, the measure of exposure was seriously biased against events that happened closer to 1960.

Another possibility is to control the characteristics that are associated with higher media exposure. Fortunately, literature on media construction and the crime coverage in general and mass murder specifically show that particularly egregious (or high profile) crimes get longer and more in-depth coverage from news organization (see Chermak, 1997). Research shows that mass homicides that involved unknown or young victims and had a higher number of casualties enjoyed more news coverage (Duwe, 2007). Based on this literature, this study controls media exposure indirectly by modeling a standardized additive index for the following event characteristics: death toll, unknown victims, assault weapon, and mental illness. Based on literature, it is expected that the higher an event scores in this index, the more news coverage or media exposure it will get; subsequently, the diffusion effect will be stronger.

Social Integration. In his discussion on egoistic suicides, Durkheim (1951) posited that suicide varies inversely with the degree of integration of religious, domestic, and political groups. Durkheim argued that religion provides protection from suicide because it promotes social interaction, shared values, and consequently creates strong social bonds. However, Durkheim also noted that the effect of religion on suicide is heterogeneous because some denominations, such as the liberal Protestants, are less effective in inhibiting antisocial behavior. Hence, the effect is not based on religion per se, but on how religious denominations treat misbehavior (Curry, 1996; Regnerus, 2003). Religion denominations that view morality categorically (most notably conservative Protestants) and treat misbehavior more seriously are more effective in controlling deviant behavior. Research on suicide and deviance has consistently shown that the measures of Protestant conservatism are more predictive of suicide than the usual measure of total church adherence (Curry, 1996; Mainmon & Kuhl, 2008; Regnerus, 2003). This protective effect intensifies in areas that enjoy high levels of conservative Protestant homogeneity (Breault, 1986; Burr & McCall, 1997; Pescolito & Georgianna, 1989; Pescolito, 1990).

Unfortunately, data on the number of adherents in Protestant conservative churches does not exist for the entire 1970-2014 time period. Therefore, this study employs the next best measure: an additive index of *number of churches per square mile* and *rate of religious adherents*. These rates are standardized and added to create the measure of *religious integration*.[12]

Durkheim hypothesized that the size and intensity of domestic life inhibits suicide and other antisocial behavior by the subordination of the individual to the collective needs of the family. Hence, married persons are more integrated than single, widowed, or divorced persons; widowed and divorced persons are more integrated than single persons. Likewise, married persons with children are more integrated than married persons without children. Another aspect of family integration is the intensity of the interaction, which according to Durkheim, is a function of the family size. *Family integration* will be measured by a latent construct based on three items: *marriage stability* (i.e., the percentage of married households), *household size* (i.e., the average family size), and *women labor-force participation* (i.e., the percentage of women in the labor force).[13]

Social Disorganization. Another important component of social integration is the intensity of communal life. A well-integrated social system provides a high degree of consensus in norms, values, and goals. It also boosts cohesiveness and social solidarity and creates a sense of belonging (Crutchfield, Geerken, & Gove, 1982). A theory that best fits the mechanisms by which neighborhoods achieve integration or lack thereof is the social disorganization theory

[12] Data on religious adherents, churches, and denominations from the survey of *Churches and Church Membership in the United States*. This survey is funded by National Council of Churches. Data is available at http://www.thearda.com.

[13] Demographic data was obtained through the National Historical Geographic Information System. Data is available at https://www.nhgis.org.

(Shaw & McKay, 1942). According to Shaw and McKay, social disorganization is a function of the economic and social structure of the system. Specifically, they argued that residential instability, low *social-economic status*, and *racial heterogeneity* break down the cohesiveness of the collective, which weakens its ability to instill and enforce consensus on its norms, values, and goals. In line with this research, this study models community integration using the following social disorganization covariates*: racial heterogeneity*, *residential instability*, and *social-economic status*. *Racial heterogeneity* is the probability that two persons randomly drawn from a state would be in different racial groups. *Residential mobility* is a standardized additive measure composed of two census variables: the percent change in the number of households and the percent change of the population above the age of five. *Social-economic status* is a construct based on the *median household income*, unemployment rate, and the *percentage of population with a bachelor's degree*.

***Control Variables*.** In this study, I also control for *economic deprivation.* Economic deprivation has consistently been linked to higher rates of both homicide and suicide (Bursik & Grasmik, 1993; Shihadeh & Ousey, 1998; Stack, 2000a, 2000b). Normally economic deprivation is measured as a combination of *percent poor* and *unemployment rates* (see Bursik & Grasmik, 1993). However, since poverty has been captured in the *social-economic scale*, this study will measure economic deprivation through *unemployment rates*. This study also controls the demographic that have been consistently shown to correlate with suicide and homicide in the United States (see Baller et al., 2001; Kpsowa et al., 1995; Stack, 2000a, 2000b). These include *the population size* (logged), *percent rural,* and percent of *population in the 15-29 age range*.

Table 2. Operationalization of Independent Variables

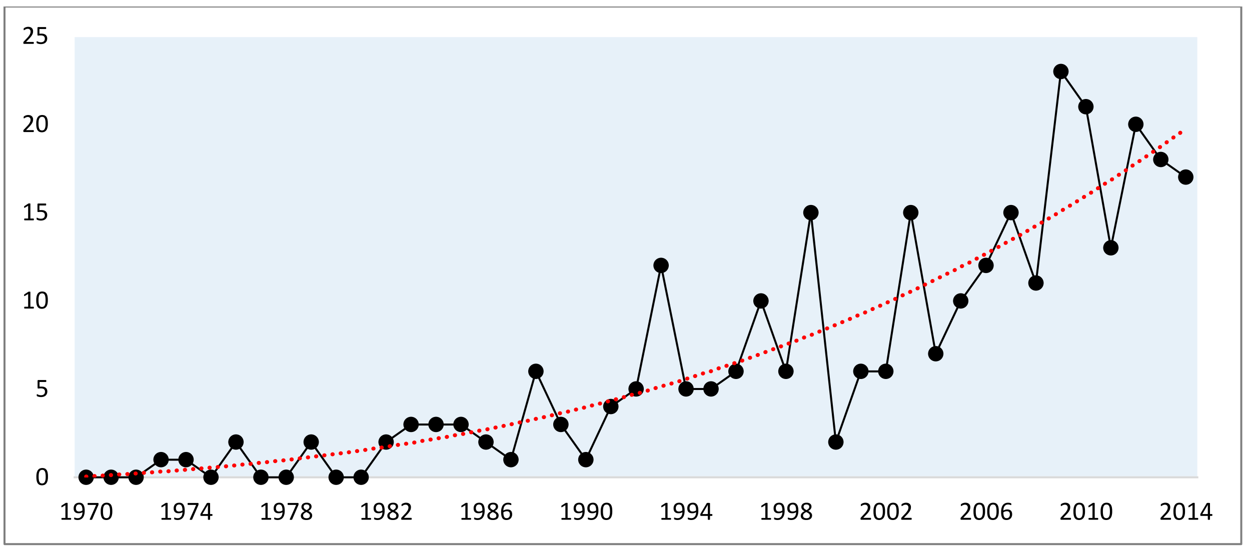
	Operationalization
Demographic Factors	
Ln(Population)	Natural log of population size
Percent 15-29	Percent of the population in the 15-29 year age bracket
Percent Rural	Percent of the population that reside in census designated rural place
Diffusion	
Spatial Lag	Average number of mass public shooting in neighboring states in the previous
Time Lag	Number of mass public shooting attacks in the last six months
Media Exposure	Scale based on: *death toll*, *unknown victims*, *assault weapon*, and *mental illness*
Social Integration	
Family Integration	Latent construct based on marriage stability, household size, and women-labor
Marriage Stability	Percent of married households
Household Size	Average family size
Women-labor	Percent of women in the labor force
Religious Integration	A standardized additive scale of church density and rate of adherents
Church Density	Number of churches per squared miles
Rate of Adherents	Number of religious adherents per 100,000 people
Social Disorganization	
SES	Latent constructed based on: median *income*, *percent BA*, and *house ownership*
Median Income	Median household income
Percent Bachelors	Percent of the population with Bachelor degree
House Owner	Percent of Housing units owned
Racial Heterogeneity	Probability of picking two persons from different racial groups
Residential Mobility	Standardized scale of *household*, and *population change*
House Change	The percent change in the number of households
Pop. Change	The percent change of the population above the age of five
Economic Depravation	
Unemployment	Percent of population 16 and over who are unemployed

CHAPTER 7
RESULTS

7.1 Exploratory Spatial Data analysis (ESDA)

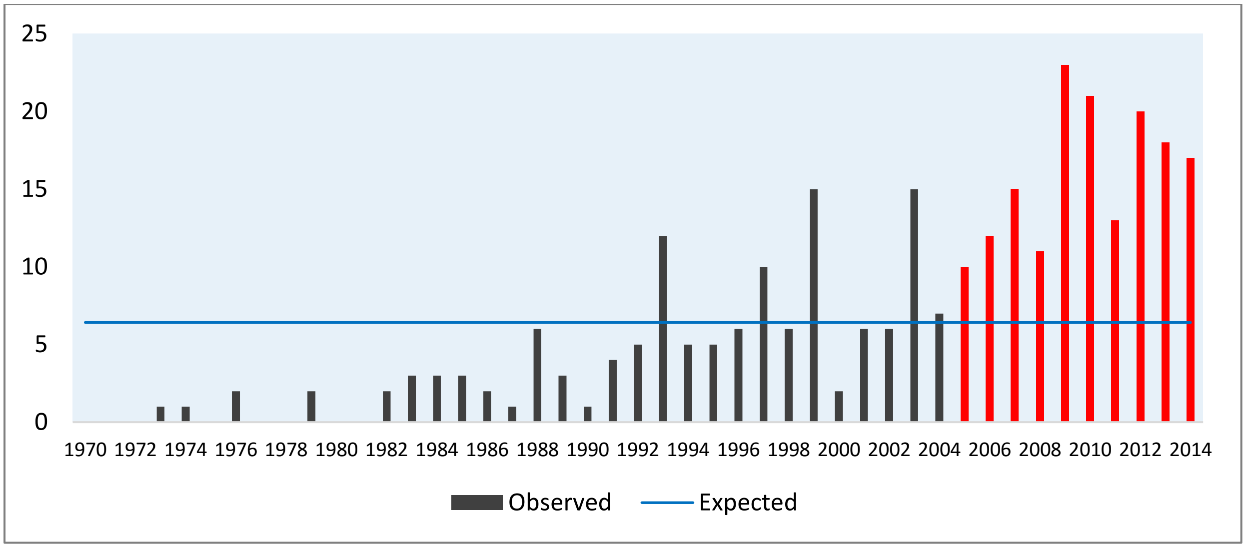
Compared to normal homicide and suicide, mass public shootings are uncommon events. From 1970 to 2014, the United States experienced 297 mass public shootings, which averages to 6.6 attacks per year. While relatively uncommon, these attacks are quite deadly. The 297 attacks resulted in 932 casualties and 1,138 injured victims. The data shows that the incidence of these attacks have been increasing steadily since 1970—almost exponentially after the year 2000 (see Figure 5). In the first 14 years of the 21st Century there have been almost twice as many shootings (196 attacks) than in the previous 30 years (101 attacks).

Figure 5. Mass Public Shootings, 1970-2014



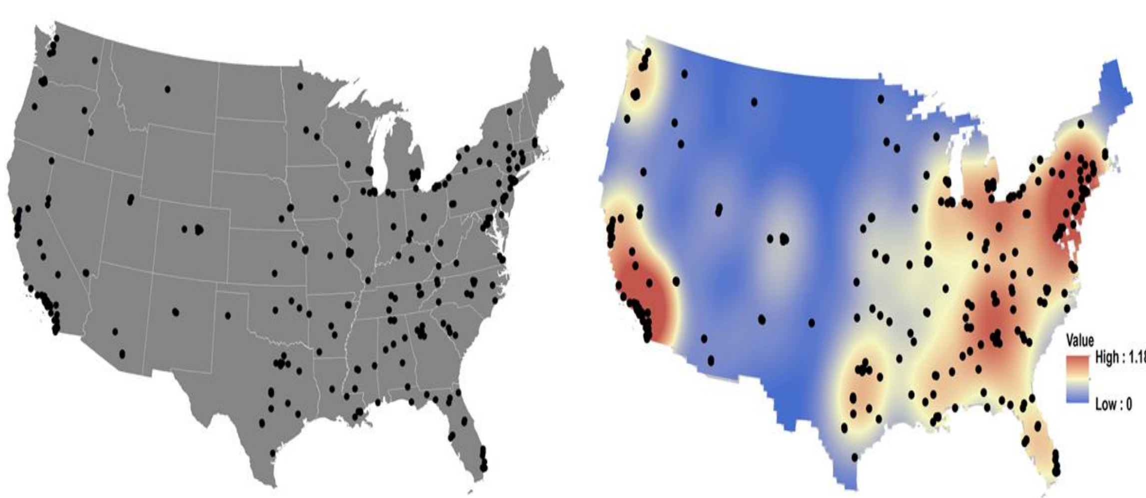
The trend line (represented by the red dotted line) is statistically significant ($z=6.05$, $p \leq 0.001$) and it suggest significant temporal clustering. A clustering corroborated by the SaTScan Time Scan Statistic (results illustrated in Figure 6). According to the scan statistic, there is one significant temporal cluster that started in the year 2005 through 2014 (Log Likelihood Ratio=74.43, $p \leq 0.001$).

Figure 6. Significant Temporal Clusters



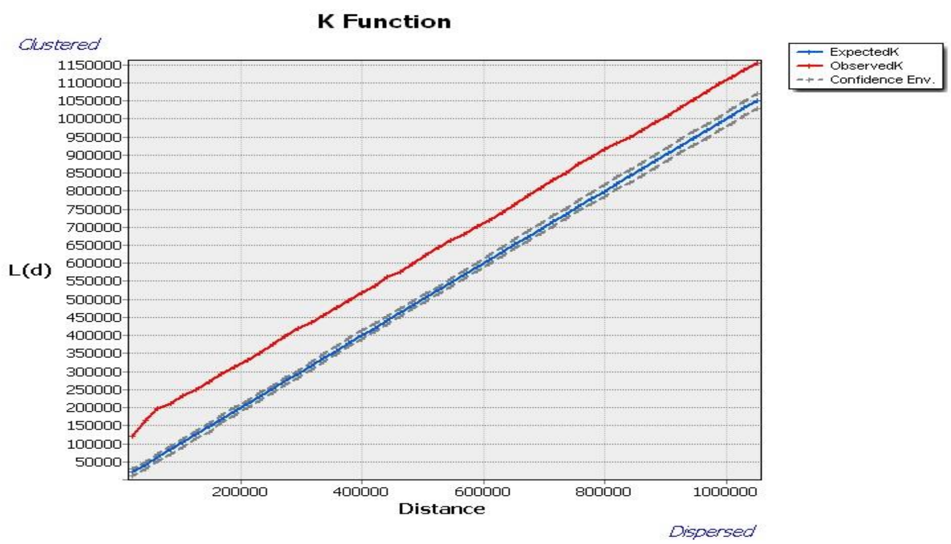
Mass public shootings also cluster in space. Figure 7 illustrates the spatial distribution of these attacks across the contiguous United States. The map on the left is a simple point map, with each point representing an attack. The map on the right, is a kernel density "heat" map, where warmer colors represent higher density of attacks or likely significant spatial clusters. Both maps show that mass public shootings cluster around the Mid-Atlantic, Appalachian Highlands, Southeast, and the Pacific Coast.

Figure 7. Spatial Distribution of Mass Public Shootings in Mainland U.S., 1970-2014



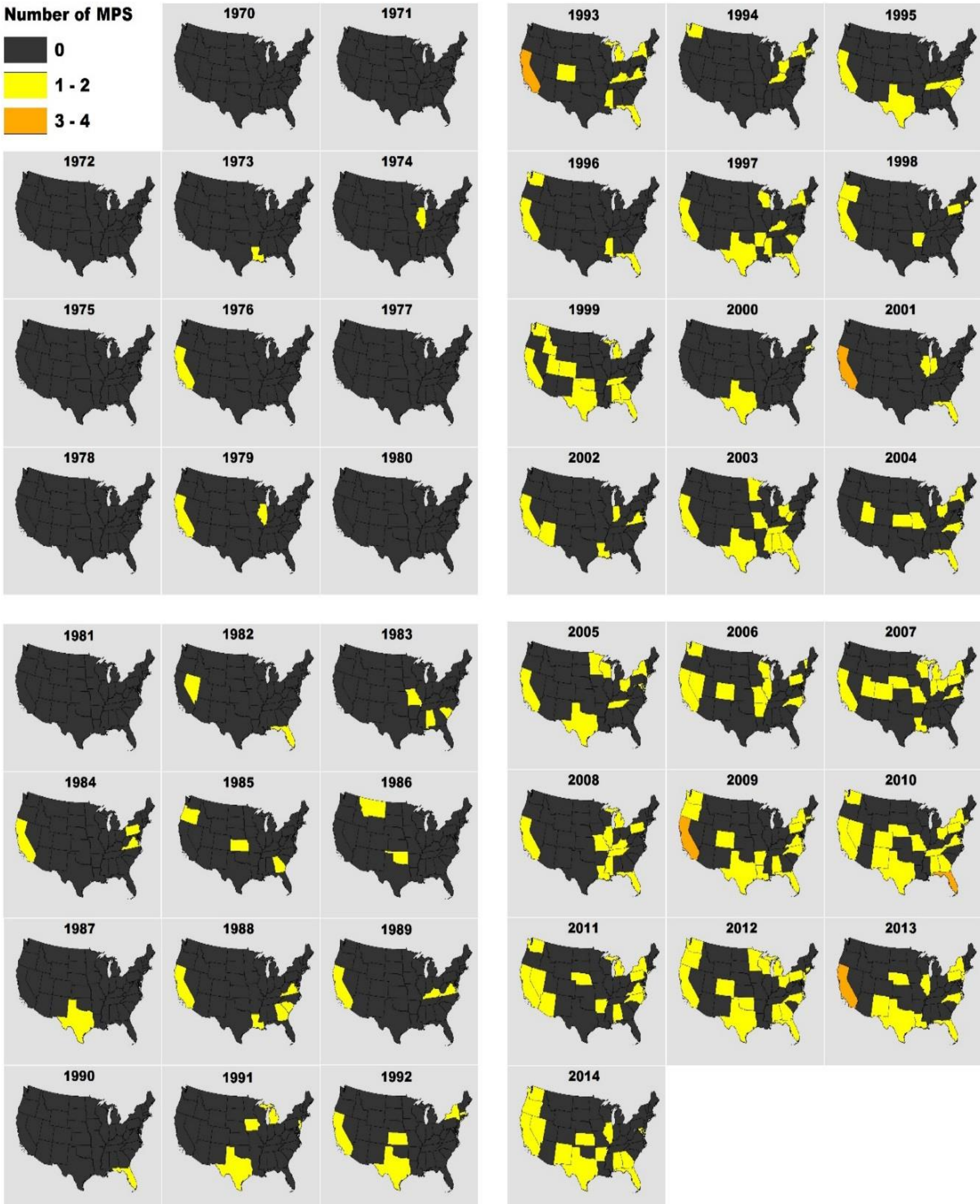
Ripley's K-Function is used to detect significant spatial clusters. Ripley's K-Function tests for clustering and dispersion over a range of distances. It evaluates feature spatial distribution in relation to Complete Spatial Randomness (CSR). In other words, it compares the K-value that is observed to the k-value that is expected under complete spatial randomness. Figure 8 presents the results from the Ripley's K-Function test. The blue line is the expected K-value under CSR. The red line is the observed K-value. The graph shows statistically significant difference between the observed and expected values. According to the results and consistent with the maps above, mass public shootings significantly cluster in space.

Figure 8. Ripley's K-Function



In addition to spatial, and temporal convergence, it is important to consider the possibility that these attacks also cluster in space *and* time. Spatial-temporal clusters result from higher than expected incidence that are highly localized in space and sustained during an extended amount of time. These clusters may reveal interesting interactions between the processes that shape the incidence of mass public shootings. Figure 9 presents the yearly number of mass public shooting attacks at the state level, from 1970-2014.

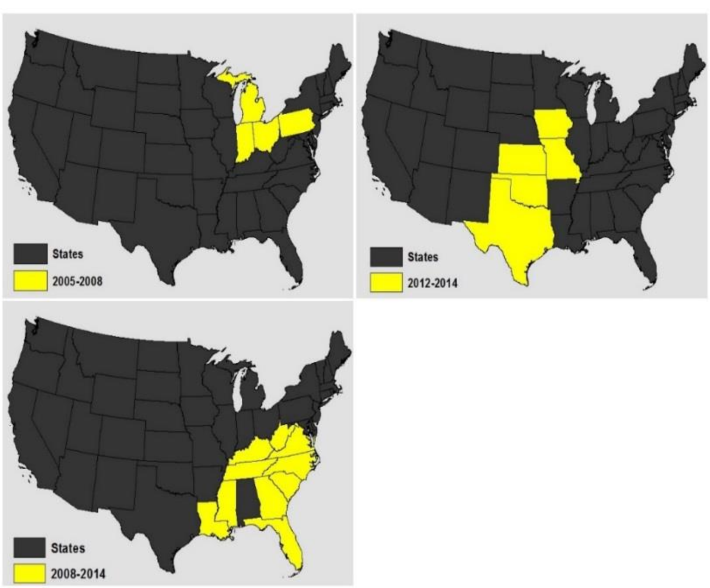
Figure 9. Number of Mass Public Shooting Attacks by State-Year, from 1970-2014



This illustration shows little spatial clustering during the 1970s, 1980s, 1990s, and early 2000s. In other words, mass public shootings tend to take place away from each other. Even when some spatial clustering occurs (e.g. 1991, 1992), the spatial convergence does not last for very long. However, there appears to be sustained spatial convergence starting in 2005 through 2014.

The SaTScan Space-Time Scan statistics identified three significant spatial-temporal clusters (see Figure 10). Consistent with the patterns above, the scan statistic located a significant space-time cluster in the Great Lake Region (Log Likelihood Ratio=11.06, $p \leq 0.05$). The cluster, which encompasses Michigan, Indiana, Ohio, and Pennsylvania, started in 2005 and lasted through 2008. The second space-time cluster encompasses the Southeast region of the United States, from Virginia to Florida and as far west as the Mississippi (Log Likelihood Ratio=15.32, $p \leq 0.001$). This cluster started in 2008 and lasted to 2014. The last space-time cluster is located in the West South Central and it stretches from Texas to Iowa (Log Likelihood Ratio=18.13, $p \leq 0.001$)

Figure 10. Significant Spatial-Temporal Clusters



7.2. Correlates of Mass Public Shootings

The Exploratory Spatial Data Analysis (ESDA) shows that mass public shootings significantly clusters in time, space, and space-time. As noted earlier, significant clustering provide evidence supporting the idea of underlying social causes. Purely individual level phenomenon should not significantly cluster in space (accounting for population density) unless it is not solely an individual level occurrence. Social integration, social disorganization and imitation/diffusion are the hypothesized processes behind the incidence and distribution of mass public shootings. In the following pages, I present a detailed examination of the social correlates of mass public shootings in the United States.

7.2.1 Social Correlates and Demographic Factors

Social integration is measured through three different constructs: *family integration, religious integration,* and *social organization.* In addition to these factors, I control for known demographic correlates of homicide and suicide, such as: *population size* (logged), *percentage of population in the 15–29 year age-range*, and *percentage of rural persons* (see Table 3 for the descriptive statistics).

Table 3. Descriptive Statistics

	Mean	Std. Deviation	Min	Max
ln(Population)	14.98	1.01	12.74	17.43
Pct. Population Age 15-29	23.27	2.69	17.78	30.36
Percent Rural	31.08	15.48	0	71.86
Family Integration	0	1	-6.34	3.6
Religious Integration	0	1	-3.01	4.75
Social-Economic Status	0	1	-4.36	5.44
Racial Heterogeneity	0.26	0.13	0.007	0.58
Residential Mobility	-0.92	0.94	-6.21	1.85
Percent Unemployed	6.26	1.58	2.71	12.58

Figure 11 presents the spatial distribution of all independent variables in the analysis. This figure show the average for the 1970-2014 time period with warner colors representing higher amounts (states colored in the lightest shade fall in the first quartile; conversely, states in the darkest shade fall in the top quartile of their distribution). Additionally, each map is overlaid with the spatial distribution of mass public shootings for the same time period.

Figure 11. Spatial Distribution of Predictors (Average for 1970-2014 Time-Period)

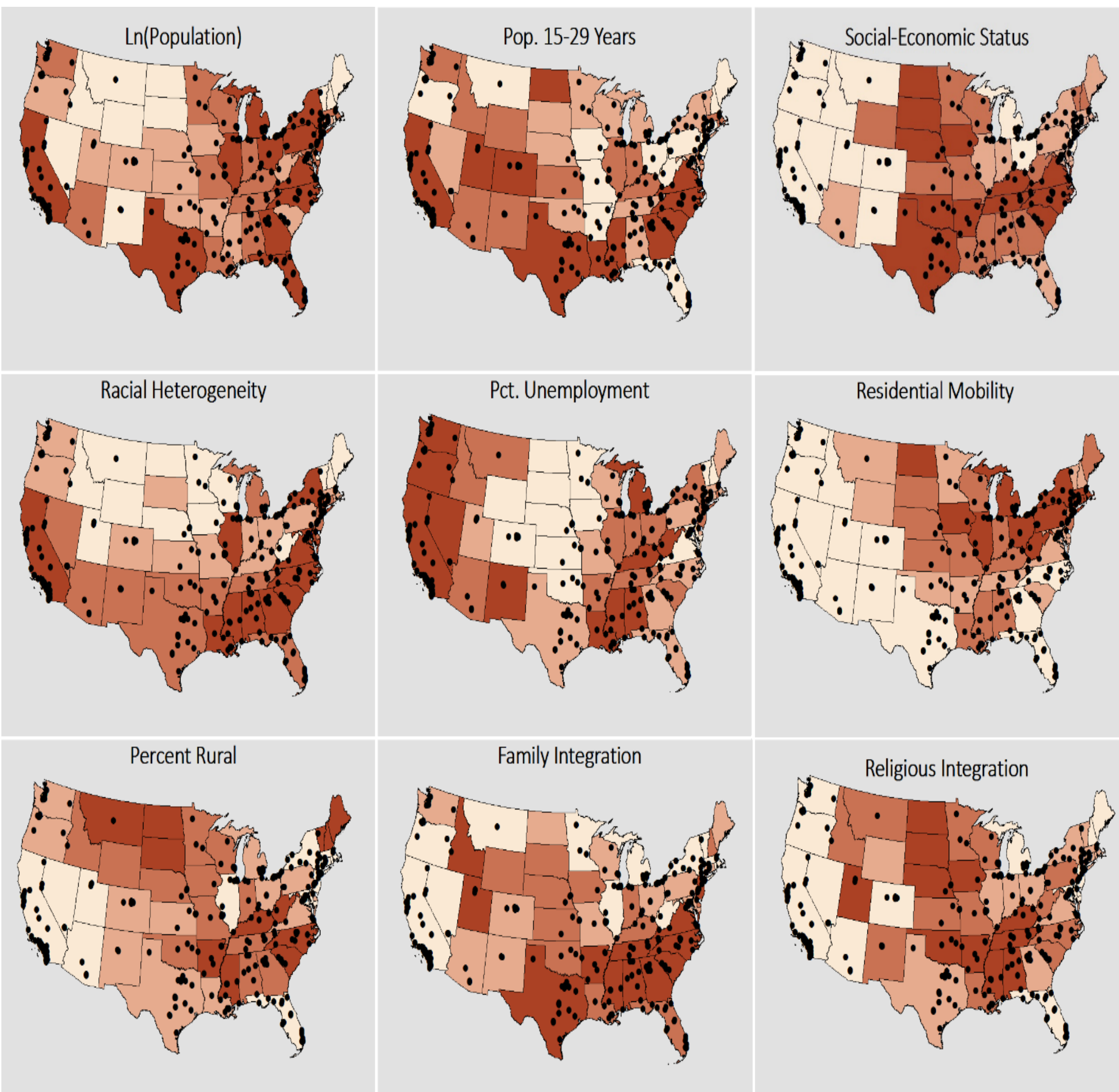


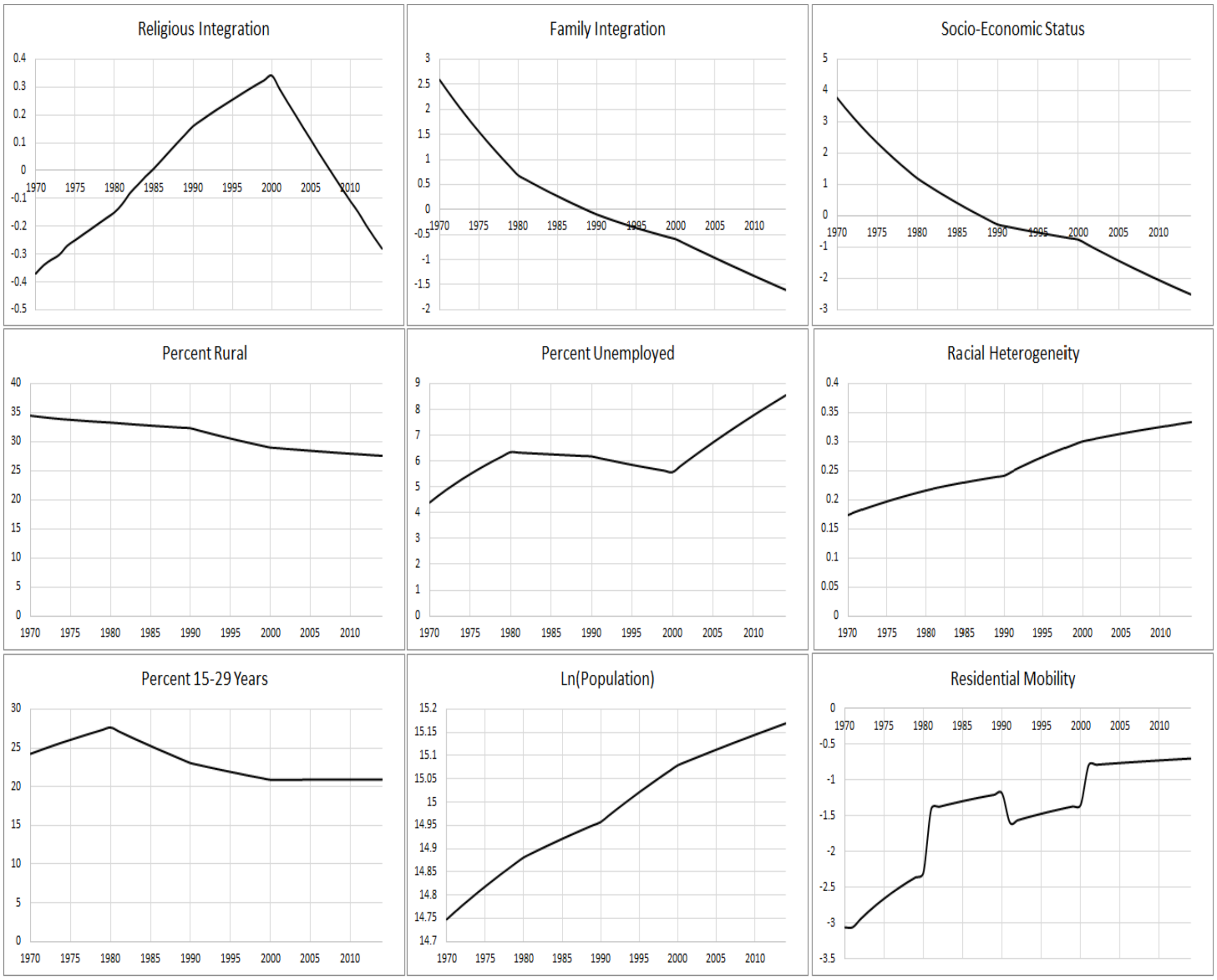
Figure 9 shows considerable spatial variation among all the predictors. From these illustrations, we see that the Northeast is characterized by high levels of *population*, as well as higher levels of *racial heterogeneity*. The Pacific Coast and Southeast regions can also be characterized by high levels of *population*, and *racial heterogeneity*, but also higher levels of *unemployment* and *percentage of 15-29 year olds*. Conversely, states with the highest percentages of *rural population* and lower levels *of racial heterogeneity* and *percent unemployment* converge in the Rocky Mountains region of the United States. The spatial variations of the demographic characteristics conform to their well-known spatial patterns.

Unlike the demographic factors, the spatial patterns of social correlates, as measured here, are not known. Even studies that have the same operationalizations do not display the spatial patterns of these social factors. Nevertheless, like the demographic factors, Figure 9 also shows considerable variation in the spatial patterns of *family* and *religious integration*, as well *social-economic status*. From the illustrations, we see that South Midwest and Southeast regions of the United States enjoy higher levels *family* and *religious integration* and *socio-economic status*. Similarly, the Midwest also enjoys high levels of *religious integration* and *socio-economic status*, but lower levels of *family integration.* The Pacific Coast, and to a certain extent, the Northeast are the only regions that consistently score lower levels on all three social correlates.

The overlay of the between the spatial distribution of predictors and mass public shootings (MPS) suggest both spatial convergence (i.e. positive correlations) and spatial divergence (i.e. negative correlations). For instance, these illustrations point to likely positive correlation between MPS and *population size, unemployment*, and *racial heterogeneity*.

Conversely, the overlays suggest negative correlations between MPS and *percent 15-29 years*, *percent rural*, and possibly *religious*, and *family integration*.

Figure 12. Temporal Trends of Demographic and Social Correlates of MPS, 1970-2014



The temporal trends (Figure 12) also reveal temporal divergence/convergence between the incidence of mass public shootings and its demographic and social correlates. But perhaps more strikingly, it shows that the year 2000 marked a significant shift in the temporal trends for most of these demographic and social correlates. For instance, *religious integration, family integration, social-economic status,* and *percent rural* began a sharp drop in the year 2000; one that continued until the end of the analysis time. Conversely, *ln(population)*, *racial heterogeneity*, *percent unemployment,* and *residential Mobility* began a substantial increase during the same time period. This shift coincides with sharp increase in the incidence of mass public shootings observed in Figure 4.

The convergence and divergence of spatial and temporal trends are confirmed by the correlation matrix presented in Table 4. The incidence of mass public shootings (MPS) is significantly and positively related with population size. Interestingly, population size is not a strong predictor of MPS; their correlation is a moderate one ($r=0.30$, $p \leq 0.05$)l; *Ln(population)* explains 9% of the total variation in the incidence of MPS. Also, the incidence of Mass public shootings also tends to be higher in states with populations that are older ($r=-0.18$, $p \leq 0.05$) and more rural ($r=0.18$, $p \leq 0.05$). As hypothesized, *family* and *religious integration* are negatively and significantly associated with the incidence of mass public shootings ($r=-0.18$, $p \leq 0.05$; $r=-0.08$, $p \leq 0.05$ respectively). In other words, the incidence of mass public shootings tend to be higher in states with lower levels of *family* and *religious integration*. It is important to note, however, that these associations are rather weak; *family* and *religious integration* explain 3% and 0.64%, respectively, of the variation in the incidence of mass public shootings.[14]

The results for the social disorganization covariates are also consistent with Durkheim's social integration theory. The incidence of mass public shootings is higher, on average, in states with lower levels of *Social-economic Status* ($r=-0.26$, $p \leq 0.05$); states with higher levels of *racial heterogeneity* ($r=0.22$, $p \leq 0.05$); and states with higher levels of *unemployment* ($r=0.22$, $p \leq 0.05$).

[14] These correlations are possibly driven downwards because mass public shootings are not normally distributed. These are rare events and such Pearson's Correlation Coefficient might not capture the true strength of associated among these variables.

Residential mobility (r=0.01, p≥ 0.05) is the only variable not significantly associated with the incidence of mass public shootings.

Table 4. Correlation Matrix

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
***MPS* [1]**									
***ln(Population)* [2]**	0.30*								
***Pct. Pop. 15-29* [3]**	-0.18*	-0.15*							
***Percent Rural* [4]**	0.18*	-0.43*	0.01						
***Family Integration* [5]**	-0.18*	0.01	0.46*	0.32*					
***Religious Integration* [6]**	-0.08*	-0.30*	0.10*	0.33*	-0.06*				
***SES* [7]**	-0.26*	-0.14*	0.62*	0.30*	0.81*	0.10*			
***Racial Heterogeneity* [8]**	0.22*	0.44*	-0.14*	-0.44*	-0.31*	0.04*	-0.35*		
***Residential Mobility* [9]**	0.01	0.02	-0.17*	0.11*	-0.28*	0.34*	-0.09*	-0.01	
***Pct. Unemployed* [10]**	0.25*	0.20*	-0.18*	-0.18*	-0.48*	-0.06*	-0.62*	0.39*	0.12*

**p≤ 0.05*

Not surprisingly, there are significant associations among the predictors as well. In fact, all but two predictors (*residential mobility* and *racial heterogeneity)* share significant correlations. While most of these correlations are weak, some are rather strong, almost to the point of statistical equivalency. For instance, there is a strong relationship between *Social-economic status*, *family integration* (r=0.80, p≤0.05) and *percent unemployment* (r=-0.62, p≤0.05). States with higher levels of *SES* enjoy, on average, high levels of *family integration* and lower levels of *percent unemployment.* These correlations are so strong that they are likely to induce multicollinearity during multivariate modeling. To fix this problem, I created indicator or 'dummy' versions of *social-economic status.* Each level represents quartile in its respective distributions. *Racial heterogeneity* is also significantly associated with *percent 15-29 years* (r=0.44, p≤0.05), *percent rural* (r=-0.44, p≤0.05), *percent unemployed* (r=0.39, p≤0.05). While these correlations are moderate, they are not high enough to induce multicollinearity.

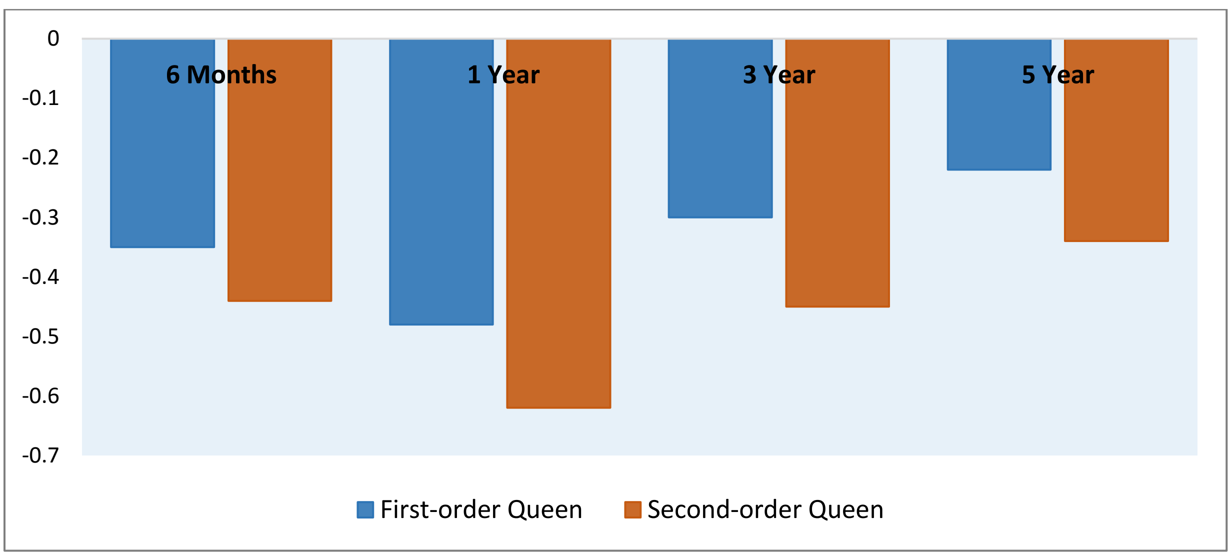
7.2.2 Imitation/Diffusion Effects

Imitation, diffusion, or neighborhood effects are measured through spatial lags. As mentioned earlier, spatial lags capture spatial dependence by lagging the value of the dependent variable one unit in space and time to capture the behavior of neighbors. In other words, spatial lags capture spatial diffusion or imitation by taking into account the behaviors of nearby states. Spatial lags make key assumptions about the process in which information and learning travel geographically (i.e. neighboring structure) and the time taken for the causal effect to run its course (i.e. time). It is impossible to know these components *a priori*. For that reason, I test a series of first and second order queen-based spatial lags that are lagged 6 months, 1, 3, and 5 years into the past.

These spatial and time lags are tested using Cox Proportional Hazard Model described in the methods section. The dependent variable for the Cox model, and all hazard models, is the hazard rate or the intensity at which these attacks occur. This intensity is measured by the time between events. The shorter the time between events, the greater the intensity; the longer the time between events the lower the intensity. Accordingly, the Proportional Cox Hazard Model estimates the predictor's effect on the hazard rate or intensity of these attacks. In other words, it estimates whether the predictor increases or decreases the risk of experiencing future attacks. (i.e. whether it shortens or expands the time between attacks).

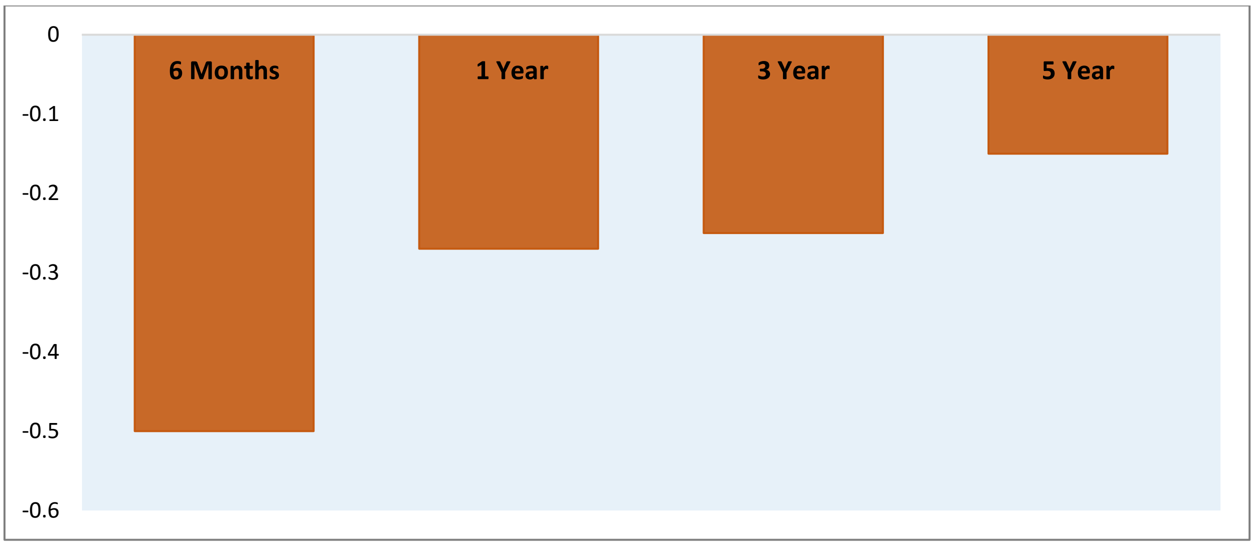
Figure 13 illustrates the predicted effect associated with the occurrence of a mass public shooting on the risk of future attacks in space (i.e. neighborhood effects), as conceptualized by the spatially lagged variables. These estimates are presented in reductions/increments in the hazard ratio. Figure 11 gives us three important pieces of information about spatial lags variables: first, there is a negative, significant, and consistent relationship between the incidence of mass public shootings and risk of future attacks. In other words, the occurrence of a mass public shooting in a state reduces the instensity or time between attacks in that state and its neighbors as defined as the spatial lag. This relationship is consistent across different conceptualization of neighborhood structures. Secondly, second-order queen-based spatial lags capture a biggger neighborhood effect than first-order queen-based spatial lags; this disparity is cosistently across different time lags. Lastly, on the matter of how far back in time these spatial lags should be set, Figure 13 shows that the biggest effect occurs when the spatial lag is set one year in the past; this is the case for first-order and second-order spatial lags. The predicted Neighborhood effects decrease when they are set at 3 and 5 years into the past. These results suggest that neighborhood effects are strongest at a 1 year time lag. Based on these results, second-order queen-based spatial lag set 1 year in the past seem to be the most appropriate measure of neighborhood effects or spatial diffusion.

Figure 13. Spatial Lags and their Predicted Effects on the Incidence of MPS



Temporal diffusion or heirarchical effects are measured by time lags. Like in autoregressive models, temporal lags lag the value of the dependent variable (*y*) by one unit in time (e.g. *t*-1). A temporal lag would be the sum of mass public shootings that have occurred in a specific interval of time. Similar to spatial lags, it is impossible to know *a priori* what the correct interval of time. In this study, I test a series of time lags that are set 6 months, 1, 3, and 5 years into the past. Figure 14 presents the predicted effects of a series of time lags on the probability of experiencing a mass public shooting.

Figure 14. Time Lags and their Predicted Effects on the Incidence of MPS



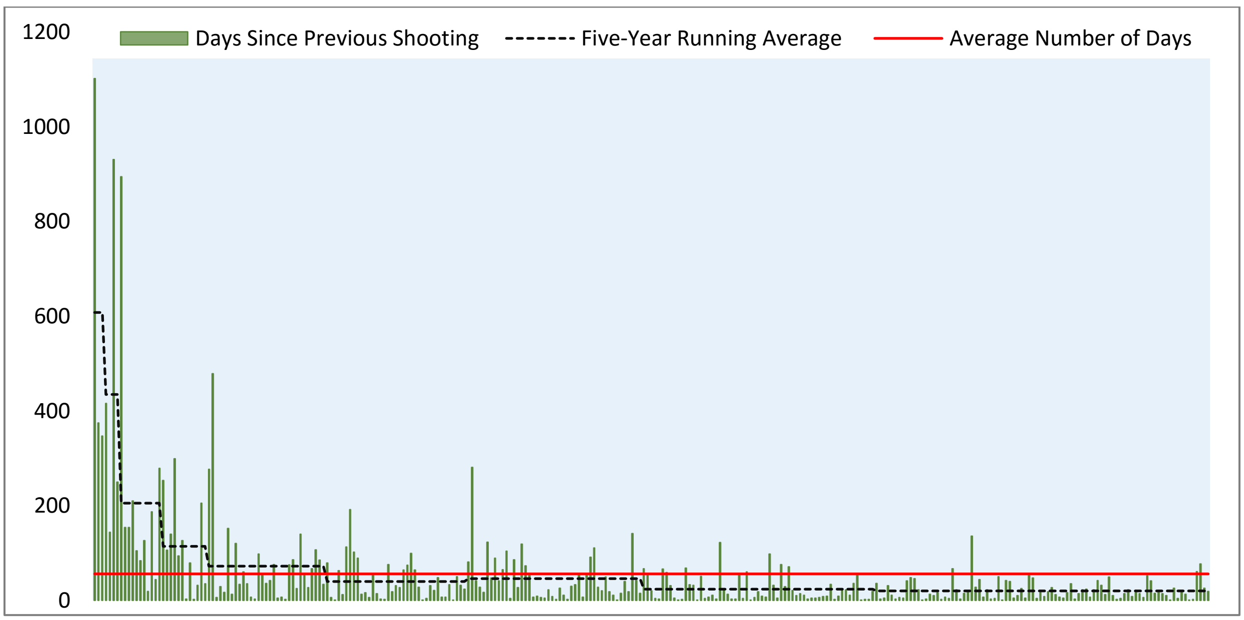
Similar to the spatial lags, the results suggests that there is a negative, and significant relationship between the time lags and the incidence of mass public shootings. That is, the occurrence of a mass public shooting, whether in the last 6 months, 1, 2, 3 and 5 years, significantly reduce the risk of future attacks. This deterrent effect is larger for the most recent time intervals and therefore, it appears that the most appropriate time lag to use in the multivariate analysis is the 6 month lag.

7.3 Event History Analysis

7.3.1 Descriptives

As noted above, the dependent variable in Event History Analysis (EHA) is hazard rate or the intensity at which events occur. This intensity is conceptualized as time between events—in this case, the time between attacks. The longer the time between attacks, the lower the intensity or hazard rate. Conversely, the shorter the time between events, the higher the intensity or hazard rate. Figure 15 presents the time timespan in days between each mass public shooting (green bars), the average number of days between shootings for the entire analysis time (red line), and five-year running-average.

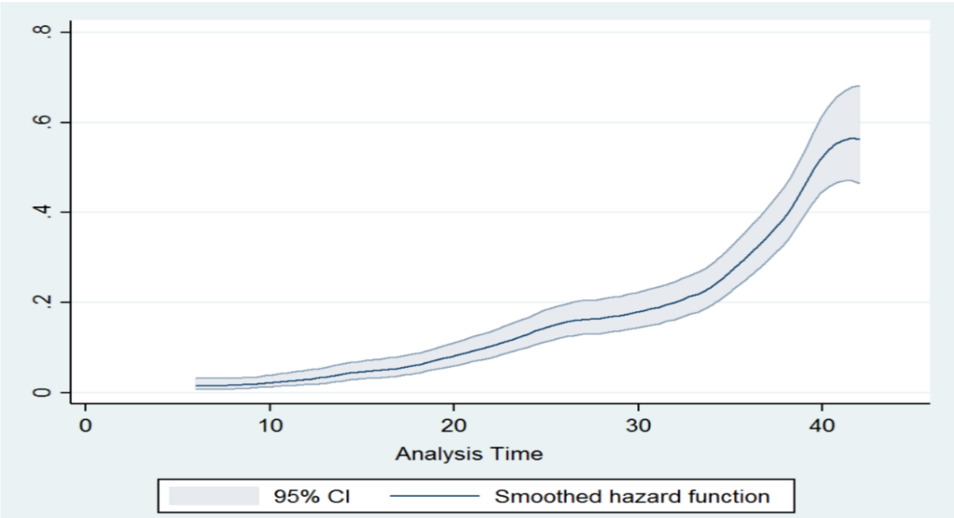
Figure 15. Number of Days since Previous Shooting



Since 1970, mass public shootings occurred, on average, every 56 days (depicted by the red line). This average, however, hides a substantial amount of variation. For instance, from 1970-1975 mass public shootings occurred on average every 608 days by 2014 the average number of days between attacks had decreased to 20. The time intervals between shootings began shrinking after mid-1990s and stayed below average for the remainder of the analysis time.

The dramatic shortening of time between attacks translate into higher intensity or hazard rate. The hazard, usually denoted as $h(t)$ is the rate at events occur. Put another way, it is the instantaneous probability that state who is under observation at a time *t* has an event at time time, given that it has survived to time to time *t*. However, at its core the hazard is a rate, not a probability. Therefore, the values of the hazard function range from zero to infinity. Figure 16 presents the smoothed hazard function for mass public shootings over the analysis time in years.[15] This illustration shows a sharp increase in the intensity or rate in which these events take place. Similar to Figure 5, the hazard estimate also shows that the incidence of mass public shootings starts to grow exponentially after the year 2000 (analysis year 30).

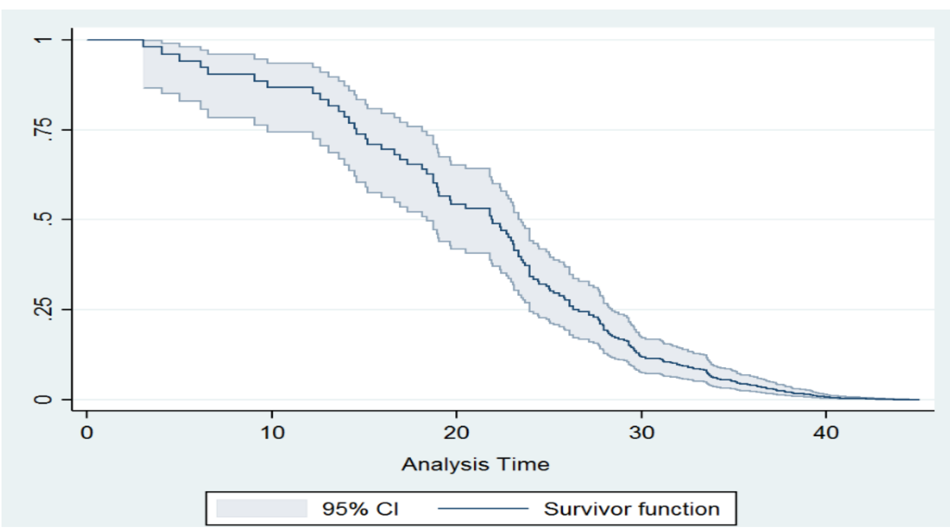
Figure 16. Smoothed Hazard Estimate



[15] The analysis time is the range of time for which states were under "observation." In this study, states began to be observed in 1970 (i.e. year 0 in the analysis time) until 2014 (year 45 in the analysis time).

In Event History Modeling, the hazard function is directly related to the survival function or $S(t)$. The Survival function is the probability of surviving (i.e. not experiencing a mass public shooting) past time *t*. The higher the hazard rate or intensity of events the shorter the expected the probability of survival. Conversely, the lower the hazard rate the higher the expected survival times. Figure 17 presents the Kaplan-Meier Survival Function estimate (a survival function table is also provided in Appendix B, table B1). The analysis begins, or the clock starts running in 1970 (analysis time=0); the probability of a state surviving or not experiencing a mass public shooting till 1980 is 0.86. In 1991, 21 years into the analysis, the United States reached the median survival time; that is, by 1990 half of all the states had experienced a mass public shooting attack. The probability of a state surviving until 2010 without experiencing an attack was 0.007. The analysis time ends in year 45, or 2014; by this time, only five states had survived or not experience an attack: New Hampshire, Maine, Rhode Island, South Dakota, and Wyoming.

Figure 17. Kaplan-Meier Survival Function



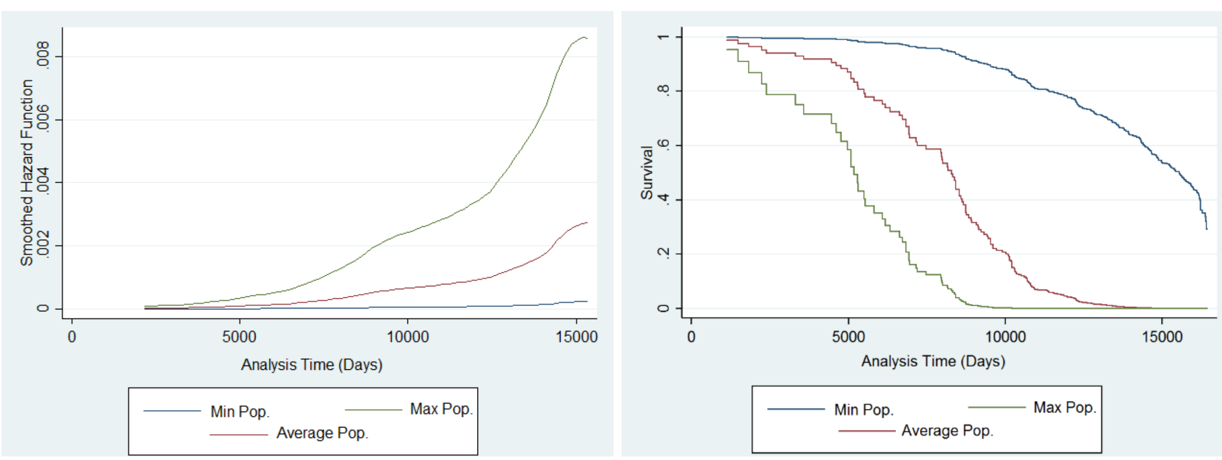
7.3.2 Multivariate Results

At the core of all hazard multivariate models is the following question: what are the factors that increase or decrease the time it takes for a failure to take place? Put in other words, in Event History Analysis, we not only interested in the shape of the hazard function and survival probabilities, we are also interested as to the factors that aggrevate or mitigate the rate at which events occur and by default which factors enlonage or shortern survival times. The Exploratory Spatial Data analysis (ESDA) suggests that social integration, and social disorganization may lower the risk of experiencing a mass public shooting. Similarly, the spatial and time lags analysis suggests that the occurrence of mass public shootings also acts as a deterrent for future attacks. This result suggests that diffusion/imitation hypothesis is wrong and that in fact the occurrence of an attack lowers the probability of future attacks. While these results are interesting, they are, however, tentative. As noted in the methods section, one cannot test either the social integration nor diffusion/imitation hypothesis without accounting for the other.

To test these hypotheses, I employ the Cox Proportional Hazards Model. Like all hazard models, the Cox model estimates the effect of predictors *on time to the event* or the hazard rate. In other words, the cox proportional hazards regression model allows for the testing of differences of survival time for different values of predictor, while holding the effects of other covariates constant. Because mass public shootings represent a "repeating event," it is possible that subject-event dependence and heterogeneity creates within-subject correlations in the timing to event failures violating the independence assumption of traditional EHA (Jones & Branton, 2005). To account for this possible dependence, I employ *robust estimation*; a widely use technique for adjusting the correlations among recurring events. This technique adjusts the estimated variances of regression coefficients for a fitted model to account for misspecification of the structured correlation (Zenger & Liang, 1986).

Table 5 presents the results from a series of Cox proportional hazard models. I apply a stepwise regression procedure to test for robustness of the estimates.[16] Model I presents the predicted effects of demographic factors on the hazard rate.[17] All demographic factors significantly predict the incidence of mass public shootings in the United States. Not surprisingly, the effect of *ln(population)* on the rate of mass public shooting is monumental. A one unit increase in log of population size is associated with a 140% $(100[2.41 - 1] = +141\%)$ increase in the rate of mass public shootings, net of everything else $(z = 8.61, p \leq 0.001)$. One can appreciate the size of this effect in Figure 18, which plots the predicted hazard and survival curves for three different levels of population: minimum, average, and maximum level of population observed in the dataset.

Figure 18. Effect of Population Size on the Hazard and Survival Functions



Note: These estimates are based on Model I

[16] In stepwise regression, covariates are entered in the regression in blocks to allow a better understanding of mediating and moderating effects. It is often used to test for the robustness of estimates. In other words, we are able to see if estimates for a predictor are consistent across different models or if they are sensitive to the inclusion of other covariates.

[17] The estimates are presented as hazard ratios, also called relative risks, to ease interpretation.

States that have large populations (like New York and California) have hazards several hundred times bigger than states with the lowest population size. The survival curve perhaps illustrates this effect better. The survival curves shows that states that have the low population levels (like Vermont and Wyoming) have much greater survival times than states with large populations. The median survival times for states with large populations is 5110 days. Conversely, states with small populations reached their median survival time about 10,000 days later.

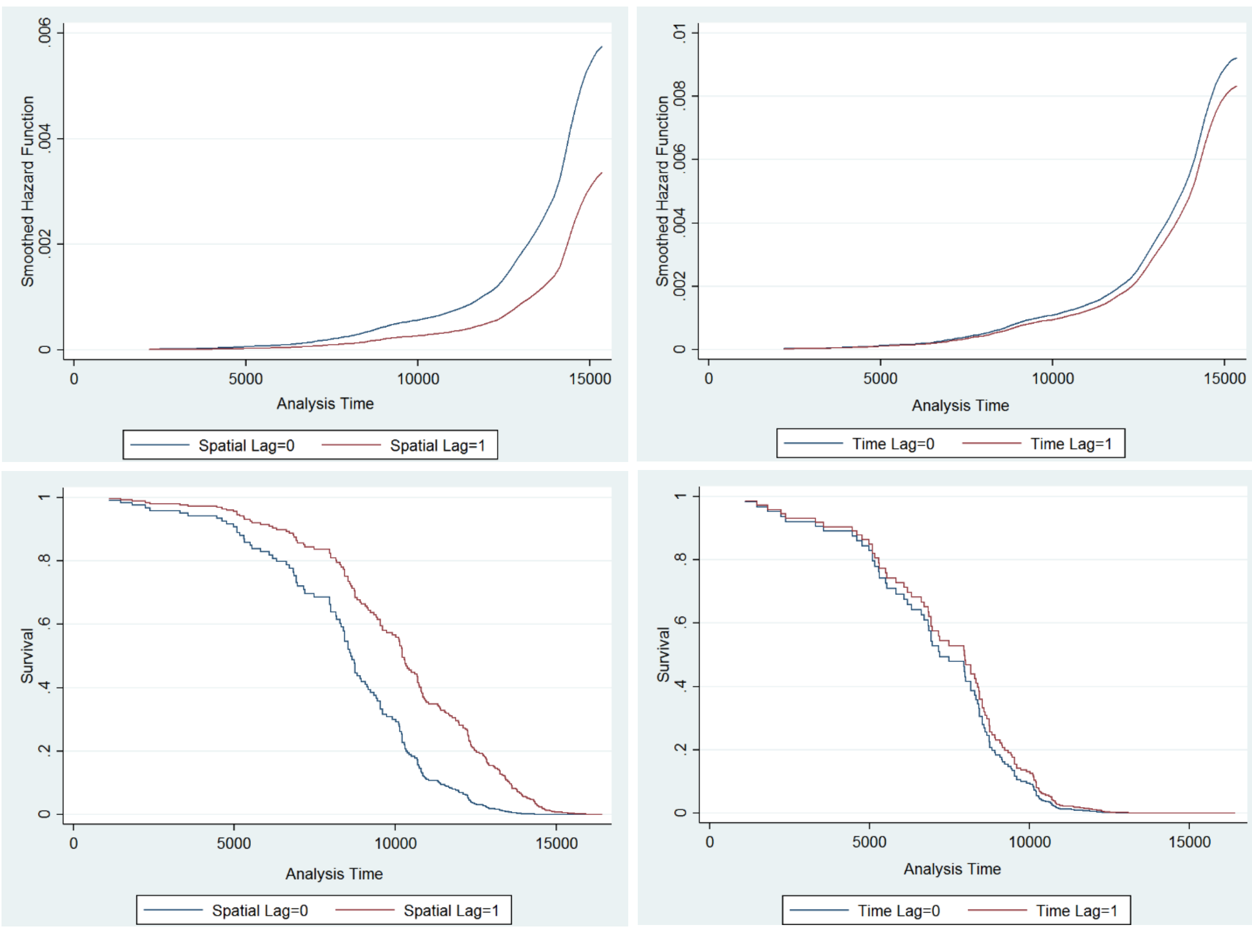
Like population size, percent of *population in the 15-29 age range* also significantly predicts the occurrence of mass public shootings ($z = 5.08, p \leq 0.001$). According the results, a one percent increase population in the 15-29 age range is associated, on average, with 40% ($100[1.40 - 1] = +40\%$) increase in the hazard rate of mass public shootings net of *ln(population)*, and *percent rural*. There is also a positive and significant relationship between *percent rural* and the incidence of mass public shootings($z = 2.44, p \leq 0.001$). Based on Model I, and all else equal, the hazard rate is expected to increase by 2% for every unit increase in a state's rural population ($100[1.02 - 1] = +2\%$). Also Table 4 presents the Akaike Information Criterion (AIC) of 1989.86.[18]

In Model II, the spatial, and time lags, along with the indirect measure of media exposure are introduced into the analysis. The results show that the spatially lagged variable and the temporal lag significantly influence of the incidence of mass public shootings ($z = -1.98, p \leq 0.05; z = -6.40, p \leq 0.001$), but not in the expected direction. Consistent with the preliminary results in section 7.2.2, the incidence of a mass public shooting attack decreases the risk of future

[18] Akaike Information Criterion (AIC) is a measure of relative quality of statistical models. By itself, the number is not meaningful. The AIC only tells us the quality of a model compared to another model in the same data. The smaller the AIC the better the quality of the model.

mass public shootings in both space and time. All else equal, the occurrence of a mass public shooting decreases the odds of a future attack in neighboring states by 53% ($0.47 - 1 \times 100 = -53\%$). This deterrent effect also occurs in time as well. The occurrence of a mass public shooting decreases the risk of future attack across the contiguous United States by 14% ($100[0.86 - 1] = -14\%$). These findings disconfirm hypotheses 6 and 7.

Figure 19. Effects Spatial and Time Lags on the Hazard and Survival Functions



Note: These estimates are based on Model II

Figure 19 illustrate the effects of a mass public shooting event on the risk of future attacks in space (spatial lag) and time (time lag). The figure clearly shows lower hazard rates and longer survival times when a mass public shooting attack has not occurred (lag=0); and higher hazard rates and shorter survival times when an attack does occur (lag=1). Combined, these results suggest that mass public shootings are not caused by imitation/diffusion as hypothesized. Contrary to the expectations, the occurrence of a mass public shooting attack creates a deterrent effect; one that is stronger or more protective near the state in which the attack took place.

A central part to the diffusion/imitation hypothesis was that of media exposure. Originally, I argued that if mass public shootings were caused by imitation/diffusion than that effect must be driven by media exposure. As discussed in the methods section, in this paper media exposure is measured indirectly through the characteristics that are linked to higher media coverage. Presumably, attacks that have more of these characteristics, which translates to more gruesome attacks, get more media coverage than those attacks that less gruesome. The results provide evidence against hypothesis 8; the results show that media exposure, as measured in this study, is not statistically ($z = -0.98, p \geq 0.05$); however, the predicted effect is consistent results of spatial and time lags. In other words, the results for the spatial and temporal lags suggest a deterrent effect. If this deterrent effect is real and driven by the media exposure, then we can expect that the more media exposure an attack gets the bigger its deterrent effect should be and the results, though not statistically significant, suggest that this might be the case.

Table 5. Results from Cox Proportional Hazard Models

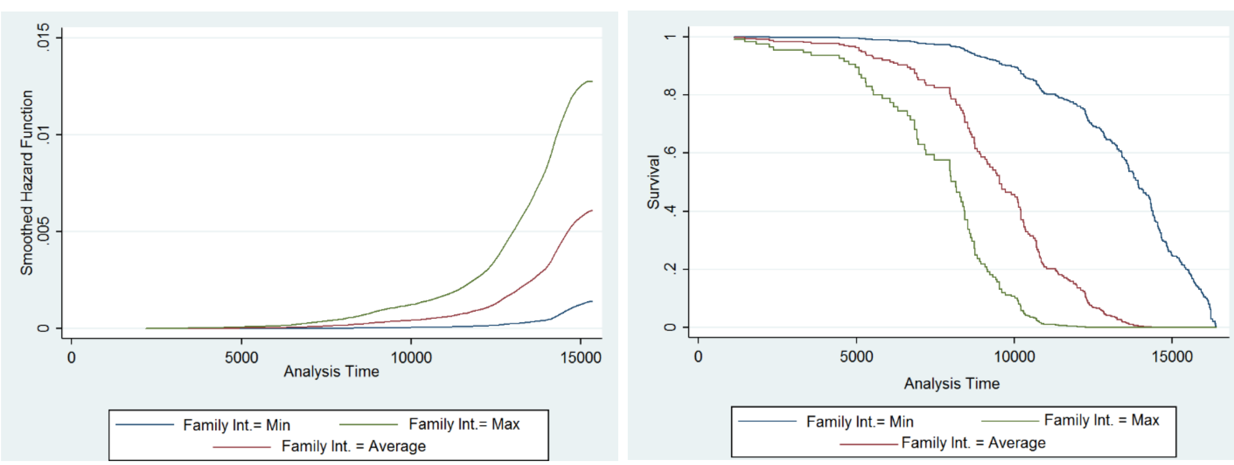
	Model I		Model II		Model III		Model IV	
	Hazard Ratios	Robust S.E.	Hazard Ratios	Robust S.E.	Hazard Ratios	Robust S.E.	Hazard Ratios	Robust S.E.
Demographic Factors								
ln(Population)	2.41†	0.246	2.11†	0.191	1.99†	0.162	1.86†	0.004
Pct. Pop. Age 15-29	1.40†	0.099	1.34†	0.089	1.40†	0.12	1.42†	0.001
Percent Rural	1.02†	0.008	1.01±	0.0075	1.02†	0.011	1.01*	0.138
Diffusion								
Spatial Lag			0.47*	0.187	0.42†	0.154	0.62±	0.134
Time Lag			0.86†	0.0185	0.86†	0.021	0.85†	0.015
Media Exposure			0.98	0.012	0.99	0.013	0.99	0.012
Social Integration								
Family Integration					1.43±	0.244	1.55 ±	0.249
Religious Integration					0.75±	0.076	0.70 ±	0.091
Social Disorganization								
SES—2 Quartile							1.75 ±	0.368
SES—3 Quartile							3.90 ±	1.301
SES—4 Quartile							8.29 ±	4.15
Racial Heterogeneity							0.32	0.27
Residential Mobility							1.34	0.278
Economic Depravation								
Percent Unemployed							1.17 ±	0.073
No. Failures	305		305		305		305	
Time at Risk	750,886		750,886		750,886		750,886	
IAC	1989.86		1935.31		1893.04		1866.04	

*$p \leq 0.05$; ± $p \leq 0.01$; † $p \leq 0.001$

The introduction of spatial, time lags, as well as the media exposure measure into the model had very little effect on the demographics block of covariates. *Ln(Population), Pct. Population Age 15-29*, and *Percent Rural* remain highly significant and their estimated effects changed only slightly. The Akaike Information Criterion (IAC) for model II is 1935.31, which represent a 103 point reduction from model I. This drop in IAC suggests that the introduction of the spatial and time lags improved model fit.

Family and *religious integration* are introduced in model III. The results suggest that contrary to expectations and correlations in Table 3, *family integration* has a significant and positive relationship to incidence of mass public shootings ($z = 5.46, p \leq 0.001$). This finding provides evidence against hypothesis 2. According to the estimates, a one standard deviation increase in *family integration* is associated with a 43% increase of the baseline hazard or risk of a mass public shooting, net demographics and spatial/temporal lags ($100[1.43 - 1] = +43\%$).

Figure 20. Effects Family Integration on the Hazard and Survival Functions

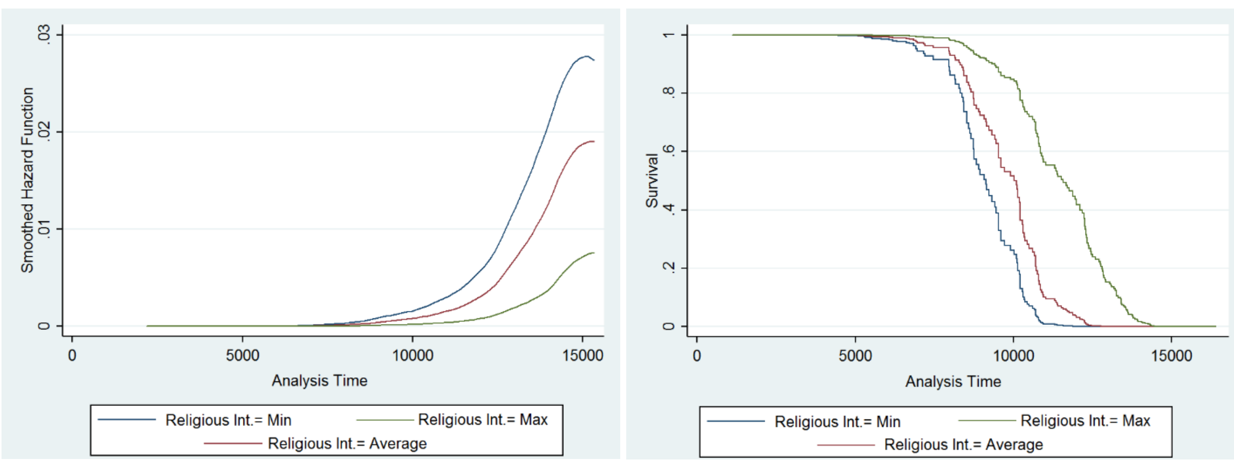


Note: These estimates are based on Model III

Figure 20 illustrates the estimated impact of varying levels of *family integration* on the hazard and survival functions. The green line represents the hazard and survival functions for a state with smallest level of family integration recorded in this study. Likewise, the red, and blue line represent the hazard/survival functions for states with average, and highest levels of family integration respectively. Contrary to expectations, states with highest levels of *family integration* are at much higher risk of experiencing a mass public shooting than those with average, and smallest levels of *family integration*.

Unlike *family integration*, the results for *religious integration* are consistent with Durkheim's social integration theory and hypothesis 1. According to the results, *religious integration* is significantly and negatively related to the risk of a mass public shooting attack ($z = 2.785, p \leq 0.01$). Net of everything else, a one standard deviation increase in religious integration is associated with a 25% decrease in the baseline hazard or risk of experiencing a mass public shooting ($100[0.75 - 1] = -25\%$). This effect is illustrated in Figure 21.

Figure 21. Effects Religious Integration on the Hazard and Survival Functions

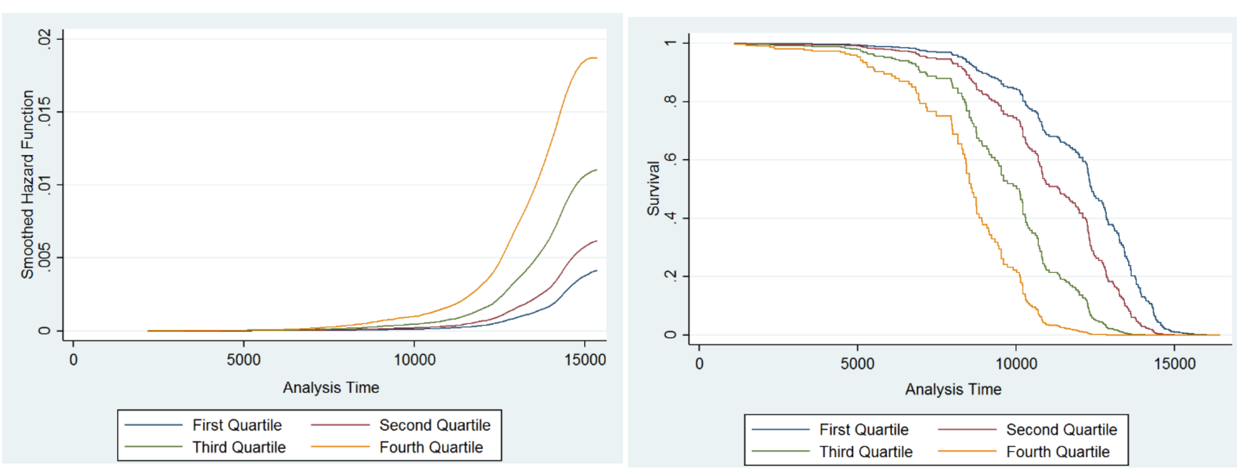


Note: These estimates are based on Model III

The results from Mode III show that including *family* and *religious integration* do not alter previous estimates. Both *demographic* and *spatial/temporal lags* are highly significant and their predicted effects, for the most part, remained unchanged; the predicted effect for *ln(population)* decreased slightly from 2.11 to 1.99. The inclusion of *family* and *religious integration* into the model reduced AIC by about 42 points, suggesting these predictors made an improvement over Model II.

The social disorganization covariates (i.e. *SES*, *racial heterogeneity*, *residential mobility*, and *unemployment*) are introduced in Model IV or the full model. The results from these covariates provide no support for hypothesized role of social disorganization on the incidence of mass public shootings. For instance, *social-economic status* is significantly and positively related to the risk of a mass public shooting ($z = 4.86, p \leq 0.01$). Not only is this finding inconsistent with the social disorganization literature and hypothesis 3, but in terms of magnitude the effect of *social-economic status* can only be compared to the effect of *ln(population)*. The magnitude of this predicted effect is illustrated in Figure 22. The results show that states in the second quartile of the *SES* distribution have a hazard rate 75% times larger than states in the bottom or first quartile of the *SES* distribution ($100[1.75 - 1] = +75\%$). Likewise, the odds of states in the top of SES distribution (4^{th} quartile) to experience a mass public are 729% times as high as those in the bottom of the SES distribution ($100[8.92 - 1] = +792\%$).

Figure 22. Effects Social-Economic Status on the Hazard and Survival Functions



Note: These estimates are based on Model IV

The results for *racial heterogeneity* and *Residential mobility* do not provide support for hypothesis 4, and 5. According to the results *Racial heterogeneity* does not have a significant effect on the risk of mass public shootings ($z = -1.35, p \leq 0.05$).[19] However, similar to *social-economic status*, its predicted is inconsistent with the literature on social disorganization and crime. *Racial heterogeneity* has traditionally being associated with higher levels of violent behavior, including homicide. However, the predicted effect for Model IV is negative. In other words, more racial heterogeneity is expected to decrease the risk of mass public shooting; or conversely, states with lower racial heterogeneity are at higher risk of experiencing a mass public shooting attack. It is important to note that this predicted effect is not statistically significant at the $\alpha = 0.05$ level and as such this estimate should be taken as suggestive at most.

Similar to *racial heterogeneity*, *residential mobility* does not significantly affect the risk of experiencing a mass public shooting($z = 1.40, p \geq 0.05$).[20] However, unlike racial *heterogeneity*, its predicted effect is consistent with the literature of social disorganization. From the results, we see that states with higher levels of residential instability are at higher risk of a mass public shooting attack. Again, it is important to note that this predicted effect is not statistically significant at the $\alpha = 0.05$ level and as such this estimate should be taken as suggestive at best.

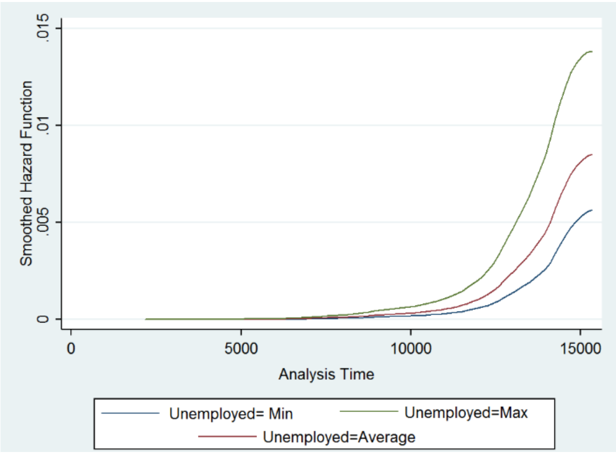
Unemployment significantly predicts the hazard of a mass public shooting attack ($z = 2.83, p \leq 0.05$). According to the results, for a one percent increase in *unemployment rate*, we

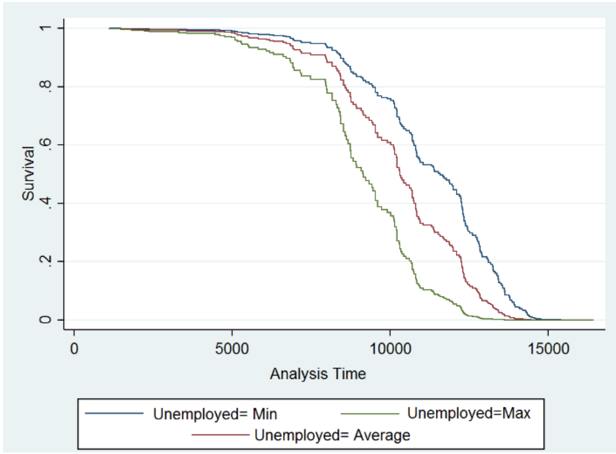
[19] However, because its *p-value* ($p = 0.15$) is very near the critical region or statistical significance, I believe it is worth discussing its estimated effect.

[20] Like *racial heterogeneity*, the estimate for *residential mobility* is also near the critical region or statistical significant($p = 0.16$). For the reasons expressed in note 16, I discuss these estimates as suggestive.

expect to see a 20% increase in the baseline hazard net of everything else $(100[1.20 - 1] = +20\%)$. The size of this effect is illustrated in Figure 2.

Figure 23. Effects of Unemployment on the Hazard and Survival Functions





Note: These estimates are based on Model IV

States with highest levels of unemployment (recorded during the analysis time) have much higher hazard rates and lower survival times than those states with average, and lowest levels of unemployment. This effect on the intensity of mass public shootings directly impacts survival times.

The estimated effects for the demographic factors, spatial/time lags, as well family and religious integration have remained consistent despite the introduction of new covariates in the regression analysis. From Model I to Model IV very little has change. Regarding demographic factors, the only predicted effect that changed noticeably is the effect of population; the effect of *ln(population)* decreased from 2.41 in Model I to 1.86 in Model. Accounting for all covariates, a one unit increase in *ln(population)* is associated with 86% increase in the hazard of experiencing a mass public shooting $(100[1.86 - 1] = +86\%)$. The estimated effects of *percent population in the 15-29 age range*, and *percent rural* have remained the same and statistically significant.

Similar to the demographic factors, the estimated effects for the spatial lag and temporal lags have also remained relatively steady through the inclusion of additional covariates. From Model II to Model IV, the hazard ratio for spatial lag decreased from 0.47 to 0.62. The predicted effect for the time lag increased from 0.86 to 0.85. Despite these small changes, the overall results still stand: the occurrence of a mass public shooting decreases the risk for future attacks. This deterrent effect is stronger near the location of the shooting.

The predicted effect for *family* and *religious integration* are also very robust. The inclusion of social disorganization covariates slightly affected the magnitude of the effects, not the direction nor their statistical significance. For instance, from Model III to Model IV, the hazard ratio for *family integration* increased from 1.43 to 1.55. Holding all covariates constant, a one standard deviation increase in *family integration* is associated with a 55% increase in the baseline mass public shooting hazard $(100[1.55 - 1] = +55\%)$. Similarly, the predicted effect for *religious integration* has increased from 0.70 in Model III to 0.75 in Model IV. Holding everything constant, a one standard deviation increase in religious integration is associated with 30% reduction in risk of a mass public shooting attack $(100[0.70 - 1] = -30\%)$.

The Akaike Information Criterion (AIC) and the negative log likelihoods have decreased with the introduction of covariates. The IAC for Model I is 1989; with the full model the IAC decreased to 1866—or a 5% reduction. This reduction suggests significant improvements over Model I.

7.3.3 Period Effects

It is important to note the the results reported above are the average estimated effects for the entire analysis period. Given the large length of time for which states under observation, it is possible that the direction, magnitude, and signficance of these effects changed through time. To account for possible 'period effects,' the data was splitted in two periods: 1970-1995 and 1996-2014.[21] The full model was estimated for each time period; the results are presented in Table 6.

Table 6. Cox P.H. Model Results for the 1970-1995 and 1996-2014 Time Period

	1970-1995		1996-2014	
	Hazard Ratio	Robust S.E.	Hazard Ratio	Robust S.E.
Demographic Factors				
ln(Population)	1.70†	0.082	1.67±	0.203
Pct. Population Age 15-29	2.3±	0.099	1.12*	0.521
Percent Rural	0.96	0.019	1.02*	0.126
Diffusion				
Spatial Lag	0.05†	0.061	0.66	0.22
Time Lag	0.99	0.134	0.85†	0.019
Media Exposure	1.01	0.134	0.98	0.014
Social Integration				
Family Integration	1.65*	0.97	1.01	0.25
Religious Integration	0.45†	0.134	0.86±	0.019
Social Disorganization				
Social-Economic Status[22]	2.1†	0.563	2.45†	0.563
Racial Heterogeneity	0.47	2.053	0.52	0.567
Residential Mobility	1.99†	0.321	0.92	0.23
Economic Depravation				
Percent Unemployed	2.27†	0.479	1.51†	0.178
Number of Failures	62		238	
Time at Risk	9449		7303	

**p≤0.05; ± p≤0.01; † p≤0.001*

The model results for the 1970-1995 time period are a bit different than the main analysis. In this time period, the predicted effects of the demographic factors are consistent with

[21] Time was split unevenly to account for the massive difference in the number of shootings that occurred after year 2000. Even with the uneven split, there are almost four times the number of shootings in the second period.

[22] Social-economic status was fitted as a continuous variable because the model for period 1 would not converge with its categorical counterpart. This is likely to the fact that there is not enough variation in SES in the 1970-1995 time period. Hence, there were not enough observations to populate each categories.

the main results, with the notable exception of *percent rural*. In this time period, *percent rural* does not significantly affect the baseline hazard of a mass public shooting$(z = 1.62, p \geq 0.05)$. Among the diffusion measures, the spatial lag is the only one that significantly affects the mass public shooting baseline hazard$(z = -2.53, p \leq 0.05)$. *Family* and *religious integration* significantly affect the risk of a mass public shooting$(z = 1.97, p \leq 0.05;\ z = -2.75, p \leq 0.05)$. Consistent with the main results, *family integration* increases the odds of a mass public shooting, whereas *religious integration* lowers it. Social disorganization theory receives more support in this period. While the findings *social-economic status* and *racial heterogeneity* are consistent with main results, the results show that for the 1970-1995 time period, *residential mobility* significantly affects the hazard of a mass public shooting attack$(z = -2.76, p \leq 0.05)$. According to the estimates, a one percent increase in *residential mobility* is associated with a 99% increase in the hazard of a mass public shooting$(100[1.99 - 1] = +99\%)$. The results for economic deprivation, measured a *percent unemployment*, are also consistent with the main results, with rising levels of *unemployment* significantly increasing the odds a mass public shooting $(z = 2.76, p \leq 0.05)$

The results for the 1996-2014 time period are more consistent with main results from the Cox model for the entire analysis time. All demographic factors are consistent with the main results. *Population*, *percent rural*, and *percent rural* significantly increase the odds the mass public shooting$(z = 3.34, p \leq 0.05;\ z = 2.03, p \leq 0.05;\ z = 1.99, p \leq 0.05)$. Interestingly, the diffusion mechanism switched in second period. Based on the results, the temporal lag is the only diffusion measure that significantly affects the mass public shooting attack $((z = -7.05, p \leq 0.05)$. For the 1996-2014 time period, *family integration* is not a significant predictor of mass public shootings $(z = 0.83, p \geq 0.05)$, where *religious integration* significantly lowers the risk of an attack ($z = -2.55, p \leq 0.05$). The estimated effects the for social disorganization and economic deprivation covariates are similar with those of reported in the main results. Similar to the main results, higher levels of *social-economic status* and *percent unemployment* increase the odds of a mass public shooting($z = 4.34, p \leq 0.05$; $z = 3.58, p \leq 0.05$); *residential mobility* and *racial heterogeneity* do not significantly affect the hazard of a mass public shooting attack($z = -0.23, p \geq 0.05$; $z = -0.52, p \geq 0.05$).

CHAPTER 8
DISCUSSION AND CONCLUSIONS

8.1 Discussion

In the last 40 years, the empirical research on mass murder, and most recently on mass public shootings, have focused exclusively on the identification and accumulation of individual risk factors (Bowers, Holmes, & Rohm, 2010; Capellan, 2015; Delisi & Scherer, 2006; Duwe, 2000, 2004, 2006; Fox & Levin, 1998, 2003, 2012; Kelly, 2012; Lankford, 2015; Levin & Madfis, 2009; Petee, Padgett, & York, 1997; Obsborne & Capellan, 2015). During this time, researchers have identified a number of recurring patterns in the individual characteristics, typologies, psychological makeup, and circumstances leading to mass public shootings. However, as fruitful as it once was, this literature has become arid as of late. A review of the most recent works in the literature would reveal that researchers are still preoccupied with the same individual characteristics, typologies, and aggravating circumstances. As a result, we find ourselves in a place where we seem to know all the individual risk factors that lead to mass public shooting, but we are unable to put them together. A drawback best illustrated by the fact that the vast majority of individuals that embody such risk factors never commit a mass public shooting or any other type of mass murder. Despite our best efforts in identifying all the individual risk factors, we lack a fundamental understanding of how these contribute to the incidence and distribution of mass public shootings in the United States.

Our inability to see the “big picture” does not stem from a lack of quality of the aforementioned literature. On the contrary, the mass murder literature is full of rigorous and illuminating studies. My argument, and ultimately the motivation for this study, is that in the last

40 years researchers have assumed that the proximate causes (i.e., factors and events closest to the attack) are the only ones that shape the incidence and distribution of these massacres. The emphasis on individual-level pathologies has become a significant obstacle in the formulation of a theoretical understanding of these massacres as the social contexts in which mass public shootings occur are abstracted from empirical considerations. The purpose of this study is to look "upstream"—away from the proximate causes, and towards the social ones. To my knowledge, this is the first study to treat mass public shootings as a macro-level social phenomenon.

This sociological investigation started with the Exploratory Spatial Data Analysis. ESDA unequivocally shows that mass public shootings significantly clusters in space, time, and space-time. Clustering, whether be spatial, temporal, or otherwise, provides significant evidence in support of the idea that social processes may be responsible for the incidence and distribution of mass public shooting in the United States. Once population size has been accounted, social phenomena caused *only* by individual factors should not cluster in space, and time. If it does, then clustering suggest that its causes are not exclusively individual, but perhaps also social.

Elkins & Simmons (2005) posit that there are three possible explanations for the clustering of social phenomena. The first possibility is that mass public shooting significantly clusters in space and/or time because the factors that lead to its incidence also clusters in space and/or time. These type of explanations are called "ecological determinants" because the presumed root causes lie *within* the society. The vast majority of theories and explanations regarding social phenomena falls under this category. Given the suicidal-murderous motivations behind mass public shootings, I employed two theoretical perspectives or internal determinants: (1) Durkheim's social integration theory; and (2) Shaw & Mckay's social disorganization theory. One theory has been used extensively to explain suicide, the other to explain violent behavior. I also employ a series of demographic factors known to be associated with the incidence of suicide and murder.

Internal determinants or explanations are at the core of most sociological inquiry. However, this type of explanations make what Brinks & Coppedge (2006) call the "closed polity" assumption. These type explanations assume that societies are self-contained units, isolated from external forces. Which leads to the second explanation for why social phenomena clusters: imitation or diffusion. Diffusion is the process by which the "prior adoption of a trait or practice in a population alters the probability of adoption of remaining non-adopters" (Strang 1991, 325). This explanation implies that the behavior within a society may be influenced by the behavior of individuals in neighboring social groups. For this reason, I use Trade's theory of imitation/diffusion to account for the possibility that the incidence of mass public shootings are driven, at least in part, by imitation. Imitation and diffusion theory have used extensively to study inward violence (i.e. suicide), and to a lesser extent, outward violence (i.e. homicide). In both instances, this perspective has brought new and exciting insights to these phenomena.

Of course, a third possibility is that the clusters of mass public shooting attacks observed in ESDA are driven by both types of processes: internal determinants and imitation/diffusion. In order to get accurate estimates for the effects of internal determinants one must also account for the influence of imitation/diffusion processes and *vice versa*. For this reason, a Cox proportional Hazard model is employed to estimate the effects of social integration, social disorganization, and imitation/and diffusion.

The results from the hazard models paint a mixed, but very interesting picture. The results show that population size is the biggest determinant of the risk of experiencing a mass public shooting. This finding is not surprising; a quick look at the spatial distribution of mass public shootings will reveal that the incidence of mass public shootings follow closely the population density of the United States. Similarly, the line graph of mass public shooting and that of population mirror each other as well. It is possible that the sharp increase in the year 2000 in mass public shootings may be driven entirely by population growth. Interestingly, however, population density is not the only thing that matters.

In addition to population, *percent of population in the 15-29 age range*, significantly affect the mass public shooting baseline hazard. States with younger populations are significantly more at risk of experiencing a mass public shooting attack. This finding is consistent with both the suicide and homicide literatures. Studies on suicide and crime across the life cycle have consistently found that younger individuals (in the 15-30 age range) are more likely to engage in inward and outward violence (Laub & Sampson, 1993; Sampson & Laub, 1992; O'Brien & Stockard, 2006; Uggen, 2000; Warr 1998; Wray et al., 2011). These individual differences also show up in macro level studies of homicide and suicide. For instance, Levitt (1999) estimates that 20% of the crime wave during the 1980-1995 period could be attributed to changes in the age structure of U.S. population. The propensity of young adults to engage in acts of violence, whether be against others or themselves, is one of the most enduring findings in social science research (Cutright & Ferquinst, 2001; O'Brien & Stockard, 2006). It appears that the incidence of mass public shootings is also subject to variations in the population age structure.

Another demographic factor that significantly affects the mass public shooting baseline hazard is *percent rural*. This finding is consistent with the suicide literature. According to the research, increasing rurality and living in agricultural communities is associated with higher rates of suicide (Beeson, 2000; Hirsch, 2006; stack, 1982). Many reasons have been posited to explain the rural-urban divide; from the strenuous farming life (Dyer, 1997), economic and social-political stress (Kurosu, 1991), ideology regarding mental illness (Buckerwalter, Smith, & Castor, 1994), to the prevalence of pesticides (Branas, Nance, Elliot, Richmond, 2004). All of these certainly may explain why mass public shootings tend to occur in more rural areas; however, greater "opportunity structure" in the form of the greater gun availability in rural areas may be the most important factor in explaining the differences in suicides rates (Hirsch, 2006). This greater opportunity structure is evident the data. For instance, 91% of all gun related deaths in rural Wisconsin were suicides, compared to 5% in their non-rural population (Hargarten, Karlson, O'Brien, Hancock, & Quebbeman, 1996). It is possible that the same opportunity structure, compounded with the social, economic problems of rural America, has resulted in a greater incidence of mass public shooting attacks.

Although mass public shootings have been traditionally treated as an extreme form of homicide, it does not share the same relationship between regular homicide and rurality. When it comes to homicide, the rural-urban divide is reversed with rural places consistently enjoying lower homicide rates than urban areas (Kowalski & Duffield, 1990). These differences are statistically significant even after controlling for the demographic, and social-economic factors associated with higher crime rates (see Cubbing, Pickle, & Fingerhut, 2000). Interestingly, rural places in America have been characterized completely differently by public health researchers and criminologists. Public health experts attribute the high suicide rates to the social isolation, social economic pressures of rural America, while criminologists associate their higher levels of social organization or collective efficacy for their lower crime rates.

One of the most surprising findings in this study is in regards to the hypothesized imitation/diffusion effect of mass public shootings. The results from the Cox model not only disconfirms the notion that there is an imitation/diffusion effect, but the results consistently show that the occurrence of a mass public shooting creates a deterrent effect. It lowers the odds of a mass public shooting occurring nearby in space by 38% and in all of the contiguous United States by 15%. While the effects of *media exposure* are not statistically significant, the estimated direction of the effect is also consistent with this idea of deterrence. According to the estimates, the more media coverage, the lower of the odds of future attacks.

The deterrence effect is certainly surprising. Imitation has been consistently found to play a significant role in suicide (Ganzeboom & Haan, 1982; Kesseler,1988; Kopping et al., 1989; Wasserman, 1983; Phillips, 1972, 1974; Stack, 1992; Yoshida et al.,1991), and homicide (Berkowitz & Macaulay, 1971; Phillips, 1983; Phillips & Hansley, 1984; Zumar, 1982). There is also anecdotal evidence that mass public shootings were, at least partly, driven by imitation/diffusion. Notorious mass murderers like Robert Smith, Thomas McIlvane have claimed that their motivations to be previous mass shootings. In addition to these incidents, at least a dozen attempted and completed mass shootings have a direct connection to the Columbine High School massacre, including the Virginia Tech shooting in 2007. Furthermore, the clustering of mass public shootings also suggested possible imitation/diffusion effects.

While the deterrence effect found in this study run contrary to expectations, they are certainly not without precedent. When investigating the spatial variations of Southern lynchings, Tolnay & Deane (1996) also found a deterrent effect; specifically, they found the number of lynchings in a particular county to be depressed by the intensity of lynchings in its neighboring counties. Tolnay & Deane (1996) gave two plausible explanations for this effect. The first possibility that the occurrence of a lynching had an effect on potential offenders. Specifically, they hypothesized that once a lynching took place, Whites in the surrounding area were satisfied with the terroristic message sent to African Americans in their own communities—eliminating the need, at least temporarily, to send their own “message.” The second possibility is that the lynching has an effect on potential victims. Tolnay & Deane (1996) hypothesize that once a lynching occurs, African Americans would change their interactions with Whites to mitigate the chance of “igniting” another massacre. Tolnay & Deane (1996) favored the former explanation.

While mass public shootings are not lynchings, they are certainly the only modern events (with the exception of terrorist attacks) that match the gruesomeness, bloodshed, and sensationalism of Southern lynchings. In other words, mass public shootings, like lynchings, are critical incidents or events that are relatively brief, involving injury, loss, or conflict of significant proportion (see Schwester, 2012). Critical incidents have the potential to create social trauma, and as a result they threaten existing societal norms, and erode the collective trust on the family, work, community, and government (Hernandez de Tubert, 2006). Because they are so sudden, and unusual, critical incidents can be quite traumatic to those closest to the victims, as well as the spectators. Burstow (2003) argues that traumatized people feel the world to be dangerous because their experience tells them the world is unsafe. These individuals blame the social institutions for failing to keep them safe, and as a result begin to rely more on themselves for their survival (Hernandez de Tubert, 2006).

Under the critical incidents perspective, it is possible that the occurrence of mass public shootings has an effect on potential victims, not on the likely offenders. As originally hypothesized, mass public shooting attacks were thought increase the likelihood that potential offenders would engage in the same type of behavior (i.e. imitation). The results, however, do not suggest that this is the case, which lead us to a second possibility: the occurrence of a mass public shooting has an effect on the potential victims. Like all critical incidents, the occurrence of mass public shooting not only creates a trauma—as sense of uncertainty—in the community where it occurs, but also across the country. Under this trauma and uncertainty, likely victims (i.e. the population at large) grow cautious; they pay more attention; they are more likely to report suspicious behaviors; more likely to take measures to protect themselves. This uncertainly could also make social institutions more cautious as well. Perhaps schools, businesses, and police department educate, as well as take extra precautions to keep individuals safe.

Of course, it is possible that mass public shooting may have an effect on potential offenders. This could be the case in two ways: first, it is possible that motivated offenders also respond to this higher level uncertainty. Higher levels alertness from potential victims may delay or discouraged altogether motivated offenders from committing such massacre. A second explanation is that offenders that have entertained or are actively planning to commit an attack are discouraged from the pain and suffering that these attacks bring into the victims and the communities in which they take place. While I favor the victim-based explanation given above, this second mechanism is also plausible. Perhaps, it is the total sum of these behaviors that accountable for deterrent effect or delay in future attacks present in the results.

Durkheim's social integration is the second major theoretical perspective tested in this study. This perspective has been used to explain the incidence and distribution of suicide, as well as homicide, and public health outcomes (see Breault & Barkey, 1982; Breault, 1986; Danigelis & Pope, 1979; Stack, 1980; Wasserman, 1984). Given suicidal tendencies of mass public shooters, this theory could bring new insights into the incidence of mass public shootings also. The results gave partial support for social integration theory, conceptualized here as *family* and *religious integration*. Contrary to expectations, *family integration* was found to increase the mass public shooting baseline hazard. In other words, the rate of mass public shooting attacks is significantly higher in states with higher levels of family integration. Conversely, *religious integration* was found to have a protective force against mass public shootings

Taken all together these findings are hard to interpret. Family integration is a key component of Durkheim's social integration thesis. Durkheim argued that the size and intensity of domestic life inhibits suicide among other antisocial behavior through the subordination of the individual ego to the collective need of the family. This argument is well supported in the literature. Divorce is not only linked to higher rates of suicide (Breault & Barkey, 1982; Breault, 1986; Danigelis & Pope, 1979; Stack, 1980; Wasserman, 1984), but also to higher crime rates, and shorten lifespans (Goldman, 1993; Sampson & Laub, 1992; Sampson, Laub &Wimer, 2006; Porter & Purser, 2010). This finding contradicts all we know about family integration.

There are several plausible explanations for this counterintuitive finding. One possibility is that the models are not accounting for a lurking variable that is correlated with family integration and incidence of mass public shootings and therefore creating the illusion of a causal relationship. Mass public shooting attacks are not an "urban," but a rural-suburban phenomenon. As we will soon discuss, mass public shootings are, by enlarge, a high social-economic status community problem. From that perspective, this finding is not counterintuitive since these communities generally have higher than average family integration (Stack, 2000b). It is likely, that the models are not picking up the culprit behind this illusion. A second possibility is that there is not enough variation at the state level to pick up the true effect of family integration. Perhaps a lower unit of analysis (e.g. county-level) might reveal the protective nature of family stability. Unfortunately, this finding will have to be explored in future studies.

The second component of social integration theory is *religious integration*. In this study religious integration is conceptualized as the intensity of religious life—i.e. average number of churches per square mile, and number of religious adherents per 100,000 people. Durkheim posited that religion provides protection from suicide because it promotes social interaction, shared values, and consequently strong social bonds. Unlike *family integration*, the findings for *religious integration* are consistent with the literature suicide and homicide (Baeir & Wright, 2001; Breault, 1986; Bainbridge, 1989; Burr & McCall, 1997; Pescolito & Georgianna, 1989; Pescolito, 1990). The results from the Cox models suggest that a one standard deviation increase in *religious integration* lowers the hazard of a mass public shooting attack by 30% net of everything else.

The third theoretical perspective used to explain the incidence of mass public shooting is Shaw & McKay's (1942) social disorganization theory. Similar to Durkheim, they argued that a well-integrated social system provides a high degree of consensus in norms, values, and goals. It also boosts cohesiveness, social solidarity, and creates a sense of belonging. Shaw & McKay's (1942) posited that social cohesion or a lack of it, what they call "social disorganization" is a function of the social and economic structure of the community, specifically: low social-economic status, high racial heterogeneity, residential instability, and economic deprivation measured as percent unemployment.

The results did not provide any support for social disorganization theory. S*ocial-economic status* was found to significantly increase the hazard of a mass public shooting attack. Everything else equal, states at the top of the distribution have a risk 792% times bigger than states at the bottom of the SES distribution. This finding is at odds with the social disorganization literature, where communities with higher levels of social-economic status, have been consistently found to have lower, not higher, homicide rates (Freisthler, 2004; Porter & Purser, 2010; Shaw & McKay, 1942; Sampson and Groves, 1989; Steenbeek, Hipp, 2011).

However, seen from the literature on suicide, the effect of SES is not at all counterintuitive. Contrary to homicide, higher levels of SES have been linked with higher rates of suicide (Platt, 1992; Simpson & Conklin, 1989; Stack, 2000b). The effect of SES, along with estimates for rurality, suggests that mass public shootings behaves more like a suicide than a homicide.

The results also show that r*acial heterogeneity*, and *residential instability* have no statistical bearing on the hazard of a mass public shooting attack. The findings for *racial heterogeneity*, and *residential instability* are also surprising given how consistently higher levels of these predictors have been found to increase homicide and other violent and property crime (Freisthler, 2004; Porter & Purser, 2010; Rose & Clear, 1998; Shaw & McKay, 1942; Sampson and Groves, 1989; Steenbeek & Hipp, 2011).

Economic deprivation, conceptualized as rate of unemployment, significantly affects the hazard of mass public shooting. According to the Cox model estimates, all else equal, the hazard rate is expected to increase by 17% for every one percent increase in unemployment rate. These findings are consistent with both the suicide and homicide literatures where higher levels of unemployment are associated with higher murder and suicide rates (Kposowa et al., 1995; Platt, 1984; Stack & Haas, 1984).

8.1.1 Period Effects

Splitting the analysis time and fitting full model in each time period provide a bit more nuance to the discussion above. Generally, the results for the 1970-1995, and 1996-2014 time periods are consistent with main results. On both periods, higher amounts of *population*, *percent in the 15-29 age bracket, social-economic status,* and *percent unemployment* to significantly increase the odds of a mass public shooting, net of everything else. Similarly, *religious integration* consistently lowers the risk of an attack on both time periods. Consistent with the main results, *media exposure* and *racial heterogeneity* have no statistical bearing on the hazard of a mass public shooting.

Despite these similarities, there are some interesting disparities in the estimated effects for these time periods. For instance, *percent rural* is not significant for the 1970-1995 period, but it is a significant predictor in the 1996-2014 time period. The results also show that *family integration* significantly affects the odds of a mass public shooting only in the 1970-1995 period. It appears that the intensity of familial life, as conceptualized here, loses significance in the last 18 years of the analysis time. Similarly, *residential mobility* is only significant in the 1970-1995 time period. The more interesting finding is regarding the diffusion covariates. The analysis shows that the deterrent effect of mass public shootings moved through spatial channels in the 1970-1995 time period, and at some point the effect was channeled through means that were not based in space. In other words, the deterrent effect if mass public shootings affected all of the contiguous United States homogeneously.

It is easy to over interpret or give too much weight to the disparities in the effects for these two time periods. It is important to realize that splitting the data in time lowers the number of observations and hence limits our ability make valid inferences about the finding. This is particularly the case for a statistical technique with time at its core. Indeed, the strength of Event History Analysis is that its estimates are based on what has happened in the both past and the future. Splitting the data only hinders its ability to make estimate valid and consistent effects. With that in mind, the differences for *percent rural*, *family integration*, and *residential mobility* may be a product of this limitation as there is no theoretical explanation that could account for the changes. However, the disparities for the diffusion effects fit very well with the diffusion mechanisms and channels.

In line similar studies on imitation, this study assumes that information that allows for a deterrent effect is being communicated by the media. In the 1970s, information flowed more locally than today as local and regional newspapers and TV news were the principal source of information. However, with the growth of national news, 24-hour news cycle, the advent of the internet, and social media, information flows much more rapidly, almost instantaneously, throughout the United States. The evolution of communication channels in the last 45 years from one that is mostly local to one that is national in nature may account the switch observed for the spatial and temporal lags.

8.2 Conclusions

This study represents the first sociological investigation of mass public shootings in the United States. Using the most comprehensive dataset of mass public shooting attacks, this study is first to formally theorize and empirically test potential social processes behind the incidence and distribution these massacres. The significance of this endeavor could be judged in two ways. If the success of this study were to be measured in how well the proposed theories explained the incidence of mass public shootings, then I would conclude the study was not very successful. Imitation/diffusion hypothesis was disconfirmed. Similarly, the analysis did not provide any support for social disorganization theory. *Racial heterogeneity* and *residential mobility* did not significantly affect the hazard of mass public shooting. Inconsistent with the crime literature, s*ocial-economic status* was found to increase the hazard of an attack. Among the three theories tested, Durkheim's social integration theory was the most successful, but also partially supported. Consistent with the social integration perspective, *religious integration* was found to depress the odds of a mass public shooting attacks. Conversely, *family integration* was found to significantly increase the risk of a mass public shooting attack.

If, however, this study were to be judged on insights we have gained, then I would conclude this to be a very successful effort—this is particularly the case for a study that has no precedent. We learned mass public shootings create a deterrence effect. The occurrence of a mass public shooting was found to depress the odds of future attacks in the surrounding areas by 38% and across the United States by 15%. This deterrent effect suggest that the clustering observed in ESDA is not due to imitation/diffusion. Rather, mass public shooting clusters in space, time, and space-time because the factors that lead to its incidence also clusters in space, time, and space-time. This is particularly the case for population size, which represents the most powerful determinant of the hazard of a mass public shooting. I suspect that one of the reasons why mass public shootings have never been examined as a sociological issue is because researchers feared that population would account for all of its spatial variation. However, this study provides much evidence to the contrary.

We also learned that mass public shootings tend occur in states that are more rural, with greater levels of marriage stability, and social-economic status. These are quite unique findings, as these relationships tend to be reversed for regular homicide. The results suggest that mass public shootings behave more like suicide, than regular homicide. Accordingly, future research should reassess the way in which mass public shootings are conceptualized and studied. Had this investigation treated mass public shootings as a homicide, and employed criminological theories only, the results would not have been as insightful.

No empirical investigations is without limitation and this one is certainly not the exception. A limitation is the use of state boundaries as the unit the analysis. These boundaries hide a great deal of variation in social-economic conditions, which might hinder our ability to detect significant effects, especially if mass public shootings is local phenomenon. Another important limitation is employing an indirect measure of media exposure. Ideally, media exposure would be measured by a scale based on the number of articles, TV news coverage, and the type of organizations (local *vs.* national) that report on these stories. Unfortunately, considerable time and financial resources are needed to methodically think and collect this information, as well as examine and test for possible sources of bias for the 45 year time period.

Despite these limitations, this study is the first to provide insights into the sociological roots of mass public shootings. As such, the results provide a springboard for the future literature. Future investigations should replicate this study at a lower unit of analysis. U.S. counties provide greater levels of variation and should be ideal for validating the results of this study. The deterrent effects of mass public shootings should be explored further. Particularly, the media exposure variable should be based on actual media coverage, not as an indirect indicator as it is conceptualized here. The causal mechanisms through which mass public shooting create a deterrent effect should also be explored. One possible way to study these mechanisms is to study the aftermath of these attacks, particularly the responses of the general populations, media, government, and other institutions. The critical incident perspective provide a great theoretical framework from which to couch this investigation, as well as formulating testable hypotheses on the causal mechanisms behind the deterrent effect.

On the theoretical front, future research should explore the suicide literature for more appropriate theoretical models. The results of this investigation suggest that criminological perspectives may be not be as fitting as theoretical frameworks on suicide. While this investigation only provided partial support for social integration, the Durkheimian perspective represents our best lead into a coherent explanation on the incidence of mass public shootings. Future research should evaluate Gibbs & Martin's (1964) status integration theory. Using

Durkheim's social integration theory as a point of departure, Gibbs & Martin's (1964) postulated that persons are in compatible statuses if their status is one that conforms to socially sanctioned expectations. Persons with incompatible statuses will have lower integration that those individuals with compatible statuses. Similar to social integration theory, Gibbs & Martin's (1958) predict an inverse relationship between status integration and suicide. Many argue that this is a more testable reformulation of social integration theory and the overwhelming evidence for this reconceptualization support this line of argument (Cutright & Fernquist, 2005; Danigelis & Pope, 1979; Gibbs, 1969, 2000; Stack, 1990, 2000b).

APPENDIX A.

Table A1. Sources used to construct the Mass Public Shooting Dataset

Government Reports
Kelly, R. (2012). Active shooter report: Recommendations and analysis for risk mitigation, 2012 edition. New York, NY: New York City Police Department.
Kelly, R. (2010). Active shooter report: Recommendations and analysis for risk mitigation. New York, NY: New York City Police Department.
Federal Bureau of Investigations (2013). A study of active shooter incidents in the United States Between 2000 and 2013. Washington, D.C.
Peer-Reviewed Articles
Lankford, A. (2013). A comparative analysis of suicide terrorists and rampage, workplace, and school shooters in the United States from 1990 to 2010. Homicide Studies, 17, 255-274.
Lankford, A. (2015). Mass shooters in the USA, 1966-2010: Differences between attackers who live and die. Justice Quarterly, 32, 360-379.
Blair, J. P., Nichols, T., Burns, D., & Curnutt, J. R. (2013). Active shooter events and response. CRC Press. Chicago.
Blair, J. P., & Schweit, K. W. (2013). A study of active shooter incidents, 2000-2013.
News Organizations
CNN-http://www.cnn.com/2013/09/16/us/20-deadliest-mass-shootings-in-u-s-history-fast-facts/
Mother Jones-http://www.motherjones.com/politics/2012/07/mass-shootings-map?page=2
Mother Jones- http://www.motherjones.com/politics/2012/12/mass-shootings-mother-jones-full-data
LA Times- http://timelines.latimes.com/deadliest-shooting-rampages/
Daily News-http://www.nydailynews.com/news/national/mass-shootings-central-american-history-article-1.1457514
Huffington Post- http://www.huffingtonpost.com/2013/09/17/mass-shootings-us_n_3935978.html
USA Today- http://www.usatoday.com/story/news/nation/2013/09/16/mass-killings-data-map/2820423/
Gawker-http://gawker.com/the-year-in-mass-shootings-1480354413
The Telegraph http://www.telegraph.co.uk/news/worldnews/northamerica/usa/10516913/Interactive-graphic-the-23-US-mass-shootings-since-Sandy-Hook.html
Dayton Daily News-http://www.daytondailynews.com/news/news/list-of-us-mass-shootings-since-1999/nTXBX/
The Telegraph-http://www.telegraph.co.uk/news/worldnews/northamerica/usa/9414540/A-history-of-mass-shootings-in-the-US-since-Columbine.html
Deseret News- http://www.deseretnews.com/top/1845/0/Tragedy-strikes-Navy-Yard-and-other-mass-shootings-in-2013.html
USA Today-http://usatoday30.usatoday.com/news/nation/mass-killings/index.html#title
Fox News-http://myfox8.com/2014/08/29/26-deadliest-mass-shootings-in-us-history/
CNN-http://www.cnn.com/2014/06/11/us/school-shootings-cnn-number/
Mother Jones-http://www.motherjones.com/politics/2014/12/fatal-school-shootings-data-since-sandy-hook-newtown

Table A1. Continued

Al Jazeera-http://america.aljazeera.com/multimedia/timeline/2013/12/timeline-of-schoolshootingssincesandyhook.html
USA Today- http://www.usatoday.com/story/news/nation-now/2014/04/19/school-shootings-timeline/7903671/
Dever Post-http://www.denverpost.com/news/ci_24721063/school-shootings-since-columbine-high-massacre
The Blaze- http://www.theblaze.com/stories/2012/12/14/conn-elementary-school-shooting-tragically-makes-list-of-worst-shooting-sprees-in-u-s-history/
Natural News- http://www.naturalnews.com/039752_mass_shootings_psychiatric_drugs_antidepressants.html
The Washington Post-http://www.washingtonpost.com/wp-srv/special/nation/us-mass-shootings-2012/
Research Organizations
Global Research-http://www.globalresearch.ca/mass-shootings-in-america-a-historical-review/5355990
Crime Prevention Research Center-http://crimepreventionresearchcenter.org/wp-content/uploads/2014/10/CPRC-Mass-Shooting-Analysis-Bloomberg2.pdf
Ballot Pedia- http://ballotpedia.org/United_States_school_shootings,_1990-present
Think Progress- http://thinkprogress.org/justice/2012/12/14/1337221/a-timeline-of-mass-shootings-in-the-us-since-columbine/
Blogs
http://www.reddit.com/r/GunsAreCool/wiki/2014massshootings
http://www.reddit.com/r/GunsAreCool/wiki/2013massshootings
http://www.reddit.com/r/GunsAreCool/wiki/2012massshootings
http://www.reddit.com/r/GunsAreCool/wiki/2015massshootings
http://shootingtracker.com/wiki/Mass_Shootings_in_2013
https://www.raptureready.com/time/massmurder.html
http://www.whiteoutpress.com/articles/q12013/list-of-45-mass-murders-and-pharma-drugs-they-were-on/
http://blog.chron.com/txpotomac/2012/12/the-list-the-deadliest-mass-shootings-in-texas-history/
Schools-Sponsored Reports
Stanford University- https://library.stanford.edu/projects/mass-shootings-america/data/data-access
Texas State University- http://www.acphd.org/media/372742/activeshooterevents.pdf
Online Encyclopedia
https://en.wikipedia.org/wiki/List_of_school_shootings_in_the_United_States
http://murderpedia.org/male.L/l/list-john-emil.htm
https://en.wikipedia.org/wiki/List_of_rampage_killers_(Americas)
https://en.wikipedia.org/wiki/List_of_school_shootings_in_the_United_States
https://en.wikipedia.org/wiki/List_of_rampage_killers
https://en.wikipedia.org/wiki/List_of_rampage_killers_(workplace_killings)
https://en.wikipedia.org/wiki/List_of_rampage_killers_(school_massacres)
https://en.wikipedia.org/wiki/List_of_familicides_in_the_United_States

Table A2. Definition and Operationalization of Variables

Variable	Definition	Measurement
Offender Characteristics		
Race/Ethnicity	Offender's Race/Ethnicity	0=White, 1= Black, 2=Latino, 3= Asian, 4=Arab, 5=Mixed
Gender	Offender's gender	0=Female, 1=Male
Age	Offender's age	
Marital Status	Offender's marital status	0=Single, 1=Relationship, 2=Married/Widowed
Familiar with Firearms	Offender's familiarity with firearms	0=No, 1=Yes
Mental Health Status	Offender's mental health status	0=No mental illness, 1=Suggested Mental Illness, 2=Confirmed mental illness
Education Level	Offender's level of education	0=HS, 1= Some college, 2= Graduate
Employment Status	Offender's employment status	0=Unemployed, 1=Employed-Blue collar, 2= Employed-White collar
Criminal Record	Offender has a criminal record	0=No, 1=Yes
Gun Ownership	Offender owned a firearm prior to attack	0=No, 1=Yes
Preparation Stage		
Precipitator	Offender experienced an event or crisis that led to the attack	0=No clear events, 1= Change of unemployment, 2= Change in relationship status, 3=Other
Acquired Firearm	Offender acquired a firearm/s in preparation for the attack	0= No, 1=Yes
Training	Offender engaged in some type of training for the attack	0= No, 1=Yes
Researched Location	Offender researched the location of the attack	0= No, 1=Yes
Discussed Plan	Offender discussed plans of the attack	0= No, 1=Yes
Surveillance of Location	Offender surveyed the location where the attack took place	0= No, 1=Yes
Level of Planning	Offender's level of planning	0=No planning, 1= Low level, 2=Medium level, 3=high level

Table A2. Continued

Variable	Definition	Measurement
Execution Stage		
Date	Date of event	
Location	Location of event	X-Y coordinates
Relationship to Target	Offender's relationship to target	0=Stranger, 1=Professional, 2= Personal
Relationship to Location	Offender's relationship to location	0= No relationship, 1=Professional, 2=Personal, 3=Other
Authorized access to Location	Offender had authorized access to location	0= No, 1=Yes
Duration of Event	Estimated duration of incident	0=Less than an hour, 1=More than an hour
Number of Injured	Number of injured victims	
Number of Fatalities	Number of fatalities	
Number of Weapons	Number of firearm used by offender	
Unknown Victims	Offender had personal relationship with at least one victim	0= No, 1=Yes
Government Target	Government institution is target	0= No, 1=Yes
Type of Firearm	Type of firearm used by offender	0= Handgun, 1= Shotgun, 2=Rifle, 3=Combination
Additional Weapons	Offender used additional, non-firearm, weapons during the attack	0= No, 1=Yes
School Shooting	Location is a school	0=No, 1=Yes
Assault	Assault Rifle used	0=No, 1=Yes
Conclusion Stage		
Surrenders	Offender surrenders to authorities	0= No, 1=Yes
Killed	Offender is killed during commission of event	0= No, 1=Yes
Suicide	Offender commits suicide	0= No, 1=Yes
Encounters Lethal Force	Offender encountered lethal force during the event (whether or not it led to death)	0= No, 1=Yes
Encounters Non-Lethal Force	Offender encountered non-lethal force during the event	0= No, 1=Yes

APPENDIX B

Table B1: Survival Table for Mass Public Shootings, 1970-2014

Time	*Fail*	*Net Lost*	*Survival Function*	*Std. Error*
3.017	1	-1	0.98	0.0198
4.044	1	-1	0.9604	0.0274
4.994	1	-1	0.9412	0.0329
6.133	1	-1	0.9224	0.0373
6.527	1	-1	0.9039	0.0408
9.076	1	-1	0.8858	0.0438
9.76	1	-1	0.8681	0.0464
12.21	1	-1	0.8508	0.0486
12.63	1	-1	0.8337	0.0505
13.05	1	-1	0.8171	0.0522
13.63	1	-1	0.8007	0.0537
13.92	1	-1	0.7847	0.0549
14.15	1	-1	0.769	0.056
14.49	1	-1	0.7536	0.057
14.54	1	-1	0.7386	0.0578
15.06	1	-1	0.7238	0.0585
15.18	1	-1	0.7093	0.0591
15.94	1	-1	0.6951	0.0596
16.63	1	-1	0.6812	0.06
16.92	1	0	0.6676	0.0603
17.31	1	-1	0.654	0.0606
18.12	1	-1	0.6406	0.0608
18.38	1	-1	0.6276	0.061
18.73	1	-1	0.6148	0.0611
18.74	1	-1	0.6022	0.0611
18.95	1	-1	0.5899	0.0611
18.96	1	-1	0.5779	0.061
19.04	1	-1	0.5661	0.0609
19.61	1	-1	0.5545	0.0607
19.7	1	-1	0.5432	0.0605
20.46	1	-1	0.5321	0.0603
21.77	1	-1	0.5213	0.06
21.79	1	-1	0.5106	0.0597
21.87	1	-1	0.5002	0.0594

Table B1: Continued

Time	*Fail*	*Net Lost*	*Survival Function*	*Std. Error*
21.91	1	0	0.49	0.0591
22.33	1	-1	0.4798	0.0587
22.37	1	-1	0.4698	0.0584
22.69	1	-1	0.46	0.058
22.79	1	-1	0.4504	0.0575
22.95	1	-1	0.441	0.0571
23.05	1	-1	0.4319	0.0566
23.07	1	-1	0.4229	0.0562
23.07	1	-1	0.414	0.0557
23.34	2	-2	0.3968	0.0547
23.5	1	-1	0.3885	0.0542
23.59	1	-1	0.3804	0.0536
23.71	1	-1	0.3725	0.0531
23.92	1	-1	0.3647	0.0526
23.93	1	-1	0.3572	0.052
23.95	1	-1	0.3497	0.0515
23.96	1	-1	0.3424	0.0509
24.16	1	-1	0.3353	0.0503
24.4	1	-1	0.3283	0.0498
24.47	1	-1	0.3215	0.0492
24.85	1	-1	0.3148	0.0486
24.99	1	-1	0.3082	0.0481
25.07	1	-1	0.3018	0.0475
25.25	1	-1	0.2955	0.0469
25.54	1	-1	0.2893	0.0463
25.78	1	-1	0.2833	0.0458
25.87	1	-1	0.2774	0.0452
26.09	1	-1	0.2716	0.0446
26.1	1	-1	0.266	0.044
26.11	1	-1	0.2604	0.0435
26.28	1	-1	0.255	0.0429
26.31	1	-1	0.2497	0.0423
26.62	1	-1	0.2445	0.0418
27.13	1	0	0.2394	0.0412

Table B1: Continued

Time	*Fail*	*Net Lost*	*Survival Function*	*Std. Error*
27.15	1	-1	0.2343	0.0406
27.43	1	-1	0.2293	0.0401
27.67	1	-1	0.2244	0.0395
27.7	1	0	0.2197	0.039
27.75	1	-1	0.2149	0.0384
27.76	1	-1	0.2102	0.0379
27.92	1	-1	0.2057	0.0373
27.95	1	-1	0.2012	0.0368
27.96	1	-1	0.1968	0.0362
27.97	1	-1	0.1925	0.0357
28.18	1	-1	0.1883	0.0352
28.22	1	-1	0.1842	0.0346
28.31	1	-1	0.1802	0.0341
28.38	1	-1	0.1763	0.0336
28.56	1	-1	0.1725	0.0331
28.76	1	-1	0.1687	0.0326
29.03	1	-1	0.1651	0.0321
29.21	1	-1	0.1615	0.0316
29.28	1	-1	0.158	0.0311
29.29	1	0	0.1545	0.0306
29.3	1	-1	0.1511	0.0301
29.38	1	-1	0.1477	0.0296
29.44	1	-1	0.1445	0.0292
29.57	1	-1	0.1413	0.0287
29.59	1	-1	0.1381	0.0282
29.61	1	-1	0.135	0.0278
29.7	1	-1	0.132	0.0273
29.7	1	-1	0.1291	0.0269
29.83	1	0	0.1262	0.0264
29.84	1	-1	0.1234	0.026
29.93	1	-1	0.1206	0.0255
29.99	1	-1	0.1178	0.0251
30.21	1	-1	0.1152	0.0247
30.98	1	-1	0.1125	0.0242

Table B1: Continued

Time	*Fail*	*Net Lost*	*Survival Function*	*Std. Error*
31.1	1	-1	0.11	0.0238
31.17	1	-1	0.1075	0.0234
31.22	1	-1	0.105	0.023
31.56	1	-1	0.1026	0.0226
31.69	1	-1	0.1003	0.0222
31.93	1	-1	0.098	0.0218
32.04	1	-1	0.0958	0.0214
32.22	1	-1	0.0936	0.0211
32.5	1	-1	0.0915	0.0207
32.51	1	-1	0.0894	0.0203
32.75	1	-1	0.0874	0.02
32.82	1	-1	0.0854	0.0196
33.15	1	-1	0.0835	0.0193
33.35	1	-1	0.0816	0.0189
33.49	1	-1	0.0797	0.0186
33.51	1	-1	0.0779	0.0182
33.54	1	0	0.0761	0.0179
33.56	1	-1	0.0744	0.0176
33.57	1	-1	0.0726	0.0173
33.63	1	-1	0.0709	0.0169
33.65	1	-1	0.0693	0.0166
33.66	1	-1	0.0677	0.0163
33.73	1	-1	0.0661	0.016
33.76	1	-1	0.0646	0.0157
33.76	1	-1	0.0631	0.0154
33.85	1	-1	0.0616	0.0151
33.94	1	-1	0.0602	0.0149
34.09	1	-1	0.0588	0.0146
34.11	1	-1	0.0574	0.0143
34.25	1	-1	0.0561	0.014
34.5	1	-1	0.0548	0.0138
34.8	1	-1	0.0535	0.0135
34.88	1	-1	0.0522	0.0132
34.93	1	-1	0.051	0.013

Time	*Fail*	*Net Lost*	*Survival Function*	*Std. Error*
35.07	1	-1	0.0498	0.0127
35.12	1	-1	0.0487	0.0125
35.15	1	-1	0.0476	0.0123
35.15	1	-1	0.0464	0.012
35.19	1	-1	0.0454	0.0118
35.3	1	-1	0.0443	0.0116
35.35	1	-1	0.0433	0.0113
35.74	1	-1	0.0423	0.0111
35.85	1	-1	0.0413	0.0109
35.89	1	-1	0.0403	0.0107
36.08	1	-1	0.0394	0.0105
36.23	1	-1	0.0385	0.0103
36.28	1	-1	0.0376	0.0101
36.29	1	-1	0.0367	0.0099
36.3	1	-1	0.0359	0.0097
36.48	1	-1	0.035	0.0095
36.64	1	-1	0.0342	0.0093
36.73	1	0	0.0334	0.0091
36.74	1	-1	0.0326	0.009
36.74	1	-1	0.0318	0.0088
36.75	1	-1	0.0311	0.0086
36.94	1	-1	0.0303	0.0084
37.03	1	0	0.0296	0.0083
37.11	1	0	0.0289	0.0081
37.12	1	-1	0.0282	0.0079
37.26	1	-1	0.0275	0.0077
37.27	1	-1	0.0268	0.0076
37.29	1	-1	0.0261	0.0074
37.32	1	-1	0.0255	0.0073
37.33	1	-1	0.0248	0.0071
37.66	1	-1	0.0242	0.007
37.72	1	0	0.0236	0.0068
37.75	1	-1	0.023	0.0067
37.76	1	-1	0.0224	0.0065

Time	*Fail*	*Net Lost*	*Survival Function*	*Std. Error*
37.77	1	-1	0.0218	0.0064
37.92	1	-1	0.0213	0.0062
37.94	1	-1	0.0207	0.0061
38.1	1	-1	0.0202	0.006
38.1	1	-1	0.0197	0.0058
38.12	1	-1	0.0192	0.0057
38.17	1	-1	0.0187	0.0056
38.19	1	0	0.0182	0.0055
38.21	1	-1	0.0177	0.0053
38.48	1	0	0.0173	0.0052
38.57	1	-1	0.0168	0.0051
38.58	1	-1	0.0163	0.005
38.79	1	-1	0.0159	0.0049
38.87	1	-1	0.0155	0.0048
39.06	1	-1	0.015	0.0046
39.12	1	-1	0.0146	0.0045
39.15	1	-1	0.0142	0.0044
39.19	1	-1	0.0139	0.0043
39.22	1	-1	0.0135	0.0042
39.23	1	-1	0.0131	0.0041
39.24	1	-1	0.0128	0.004
39.25	1	-1	0.0124	0.0039
39.27	1	-1	0.0121	0.0038
39.29	1	-1	0.0118	0.0038
39.32	1	-1	0.0114	0.0037
39.41	1	0	0.0111	0.0036
39.41	1	-1	0.0108	0.0035
39.44	1	-1	0.0105	0.0034
39.5	1	-1	0.0102	0.0033
39.56	1	-1	0.0099	0.0032
39.59	1	-1	0.0097	0.0032
39.69	1	-1	0.0094	0.0031
39.84	1	-1	0.0091	0.003
39.85	1	-1	0.0089	0.0029

Table B1: Continued

Time	*Fail*	*Net Lost*	*Survival Function*	*Std. Error*
39.85	1	-1	0.0086	0.0029
39.86	1	-1	0.0084	0.0028
39.91	1	-1	0.0082	0.0027
40.01	1	-1	0.0079	0.0027
40.02	1	0	0.0077	0.0026
40.03	1	-1	0.0075	0.0025
40.11	1	-1	0.0073	0.0025
40.15	1	-1	0.0071	0.0024
40.15	1	-1	0.0069	0.0024
40.17	1	-1	0.0067	0.0023
40.18	1	-1	0.0065	0.0022
40.3	1	-1	0.0063	0.0022
40.43	1	-1	0.0061	0.0021
40.55	1	-1	0.0059	0.0021
40.61	1	-1	0.0058	0.002
40.62	1	-1	0.0056	0.002
40.62	1	-1	0.0054	0.0019
40.66	1	0	0.0053	0.0019
40.69	1	-1	0.0051	0.0018
40.73	1	-1	0.005	0.0018
40.74	1	-1	0.0048	0.0017
40.76	1	-1	0.0047	0.0017
40.77	1	-1	0.0046	0.0016
40.95	1	-1	0.0044	0.0016
41.01	1	-1	0.0043	0.0016
41.02	1	0	0.0042	0.0015
41.06	1	-1	0.004	0.0015
41.11	1	0	0.0039	0.0014
41.48	1	-1	0.0038	0.0014
41.56	1	-1	0.0037	0.0014
41.68	1	-1	0.0036	0.0013
41.7	1	-1	0.0035	0.0013
41.76	1	-1	0.0033	0.0012
41.77	1	-1	0.0032	0.0012

Table B1: Continued

Time	*Fail*	*Net Lost*	*Survival Function*	*Std. Error*
41.78	1	-1	0.0031	0.0012
41.91	1	-1	0.003	0.0011
41.92	1	-1	0.0029	0.0011
42.03	1	-1	0.0029	0.0011
42.14	1	-1	0.0028	0.0011
42.15	1	0	0.0027	0.001
42.18	1	-1	0.0026	0.001
42.25	1	-1	0.0025	0.001
42.26	1	0	0.0024	0.0009
42.41	1	-1	0.0023	0.0009
42.54	1	-1	0.0023	0.0009
42.55	1	0	0.0022	0.0009
42.59	1	-1	0.0021	0.0008
42.61	1	-1	0.002	0.0008
42.66	1	-1	0.002	0.0008
42.74	1	0	0.0019	0.0008
42.77	1	-1	0.0018	0.0007
42.79	1	0	0.0018	0.0007
42.8	1	0	0.0017	0.0007
42.85	1	-1	0.0016	0.0007
42.94	1	-1	0.0016	0.0006
42.95	1	0	0.0015	0.0006
42.99	1	-1	0.0015	0.0006
43.05	1	-1	0.0014	0.0006
43.12	1	-1	0.0013	0.0006
43.13	1	-1	0.0013	0.0005
43.2	1	0	0.0012	0.0005
43.31	1	-1	0.0012	0.0005
43.4	1	-1	0.0011	0.0005
43.43	1	-1	0.0011	0.0005
43.56	1	-1	0.001	0.0004
43.59	1	0	0.001	0.0004
43.6	1	-1	0.001	0.0004
43.61	1	0	0.0009	0.0004

Table B1: Continued

Time	*Fail*	*Net Lost*	*Survival Function*	*Std. Error*
43.65	1	-1	0.0009	0.0004
43.71	1	0	0.0008	0.0004
43.73	1	0	0.0008	0.0003
43.79	1	-1	0.0008	0.0003
43.82	1	-1	0.0007	0.0003
43.84	1	0	0.0007	0.0003
43.98	1	0	0.0006	0.0003
44.1	1	-1	0.0006	0.0003
44.14	1	-1	0.0006	0.0003
44.18	1	0	0.0005	0.0003
44.22	1	-1	0.0005	0.0002
44.25	1	0	0.0005	0.0002
44.25	1	0	0.0005	0.0002
44.32	1	0	0.0004	0.0002
44.33	1	0	0.0004	0.0002
44.39	1	0	0.0004	0.0002
44.42	1	-1	0.0003	0.0002
44.43	2	0	0.0003	0.0001
44.43	1	0	0.0002	0.0001
44.6	1	0	0.0002	0.0001
44.81	1	0	0.0002	0.0001
44.88	1	0	0.0002	0.0001
44.93	1	0	0.0001	0.0001
44.99	0	5	0.0001	0.0001

References

Abrutyn, S., & Mueller, A. S. (2014). Are suicidal behaviors contagious in adolescence? Using longitudinal data to examine suicide suggestion. *American Sociological Review*, *79*, 211-227.

Aitken, L., Oosthuizen, P., Emsley, R. & Seedat, S. (2008). Mass murders: Implications for mental health professionals. *International Journal of Psychiatry in Medicine 38*, 261-269.

Akers, R. L. (2013). *Criminological theories: Introduction and evaluation*. New York, NY: Taylor & Francis Group.

Anselin, L. (1988). *Spatial econometrics: methods and models* (Vol. 4). Springer Science & Business Media.

Bainbridge, W.S. (1989). The religious ecology of deviance. *American Sociological Review, 4,* 288-295.

Baier, C. J., & Wright, B. R. (2001). "If you love me, keep my commandments": A meta-analysis of the effect of religion on crime. *Journal of Research in Crime and Delinquency*, *38*, 3-21.

Bandura, A. (1977). *Social Learning Theory*. Englewood Cliffs, N.J.: Prentice-Hall.

Barkan, S.E., Rocque, M., & Houle, J. (2013). State and regional suicide rates: A new look at an old puzzle. *Sociological Perspectives, 56,* 287-297.

Baron, J. N., & Reiss, P. C. (1985). Same time, next year: Aggregate analyses of the mass media and violent behavior. *American Sociological Review*, 347-363.

Beeson, P. G. (2000). Some notes and data on rural suicide. *Rural Mental Health*, *25*, 13-15.

Berks, B.B. (2006). Macro-micro relationships in Durkheim's analysis of egoistic suicide. *Sociological Theory, 24*, 58-80.

Berkowitz, L., & Macaulay, J. (1971). The contagion of criminal violence. *Sociometry*, 238-260.

Berry, F. S., & Berry, W. D. (1990). State lottery adoptions as policy innovations: An event history analysis. *American political science review*, *84*, 395-415.

Blair, J. P., & Martaindale, M. H. (2013). *United States active shooter events from 2000 to 2010: Training and equipment implications*. Texas State University.

Block, C.R. & Block, R.L. (1991). Beginning with Wolfgang: An agenda for homicide research. *Journal of Crime & Justice, 14*, 31-70.

Bollen, K. A., & Phillips, D. P. (1981). Suicidal motor vehicle fatalities in Detroit: a replication. *American Journal of Sociology*, *87,* 404-412.

Bowers, T.G., Holmes, E.S., & Rhom, A. (2010). The nature of mass murder and autogenic massacre. *Journal of Criminal Psychology, 25*, 59-66.

Box-Steffensmeier, J.M., & Jones, B.S. (2004). *Event history modeling: A guide for social scientist.* New York, N.Y.: Cambridge University Press.

Box-Steffensmeier, J. M., De Boef, S., & Joyce, K. A. (2007). Event dependence and heterogeneity in duration models: the conditional frailty model. *Political Analysis*, *15*(3), 237-256.

Braga, A. A., Piehl, A. M., & Kennedy, D. M. (1999). Youth Homicide in Boston: An Assessment of Supplementary Homicide Report Data. *Homicide Studies*, 3, 277-299.

Branas, C.C., Nance, M.L., Elliott, M.R., Richmond, T.S., & Schwab, C.W. (2004). Urban-rural shifts in intentional firearm death: Different causes, same results. *American Journal of Public Health, 94,* 1750–1755.

Brantingham, P. J., & Brantingham, P. L. (Eds.). (1981). *Environmental criminology* (pp. 27-54). Beverly Hills, CA: Sage Publications.

Breault, K. D. (1986). Suicide in America: A test of Durkheim's theory of religious and family integration, 1933-1980. *American Journal of Sociology, 92,* 628-656.

Breault, K. D., & Barkey, K. (1982). A comparative analysis of Durkheim's theory of egoistic suicide. *Sociological Quarterly*, *23*, 321-331.

Buckwalter, K., Smith, M.,&Castor, C. (1994). Mental and social health of the rural elderly. In R. Coward, C.N. Bull, G. Kubulka, & J. Gallchu (Eds.), *Health services for rural elders* (pp. 203–232). New York: Apresquer.

Burstow, B. (2003). Toward a radical understanding of trauma and trauma work. *Violence against women*, *9*, 1293-1317.

Butcher, F., Galanek, J. D., Kretschmar, J. M., & Flannery, D. J. (2015). The impact of neighborhood disorganization on neighborhood exposure to violence, trauma symptoms, and social relationships among at-risk youth. *Social Science & Medicine*, *146*, 300-306.

Capellan, J.A. (2015). Lone wolf terrorist or deranged shooter? A study of Ideological Active Shooters Events in the U.S., 1970-2014. *Studies in Conflict and Terrorism, 38,* 395-413.

Center for Disease Control. (2004). Married Adults are the Healthiest. www.cdc.gov.

Chermak, S. M., Freilich, J. D., Parkin, W. S., & Lynch, J. P. (2012). American terrorism and extremist crime data sources and selectivity bias: An investigation focusing on homicide events committed by far-right extremists. *Journal of quantitative criminology, 28*,191-218.

Costa, R. (2013). Losing the will to live. *USA Today*. Retrieved from: http://www.usatoday.com/story/opinion/2013/01/28/suicide-mass-murder/1872833/

Cornish, D. B. (1994). *The procedural analysis of offending and its relevance for situational prevention. In: R. V. Clarke (ed.) Crime Prevention Studies (Volume 3). Monsey, NY: Criminal Justice Press, pp. 151-196.*

Crutchfield, R. D., Geerken, M. R., & Gove, W. R. (1982). Crime rate and social integration-The impact of metropolitan mobility. *Criminology, 20*, 467-478.

Cubbin, C., Pickle, L. W., & Fingerhut, L. (2000). Social context and geographic patterns of homicide among US black and white males. *American Journal of Public Health*, *90*, 579–587.

Curry, T. R. (1996). Conservative Protestantism and the perceived wrongfulness of crimes: A research note. *Criminology, 34,* 453-467.

Cutright, P., & Fernquist, R.M. (2001). The age structure of male suicide rates: measurement and analysis of 20 developed countries, 1955-1994. *Social Science Research, 30,* 627-3640.

Cutright, P., & Fernquist, R. M. (2005). Marital status integration, psychological well-being, and suicide acceptability as predictors of marital status differentials in suicide rates. *Social Science Research*, *34*, 570-590.

Day, L. H. (1987). Durkheim on religion and suicide-a demographic critique. *Sociology*, *21, 449-461.*

De Smith, M. J., Goodchild, M. F., & Longley, P. (2007). *Geospatial analysis: a comprehensive guide to principles, techniques and software tools*. Troubador Publishing Ltd.
Cypress, M. (2004). Looking upstream. *Diabetes Spectrum*, *17*, 249-253.

Danigelis, N., & Pope, W. (1979). Durkheim's theory of suicide as applied to the family: An empirical test. *Social Forces*, *57*, 1081-1106.

Delisi, M. & Scherer, A.M. (2006). Multiple Homicide Offenders: Offense Characteristics, Social Correlates, and Criminal Careers. *Criminal Justice Behavior*, *33*, 367-391.

Dietz, P. E. (1986). Mass, serial, and sensational homicides. *Bulletin of the New York Academy of Medicine, 62*, 477-491.

Durkheim, E. (1951). *Suicide: A study in Sociology.* (J.A. Spaulding & Simpson). New York, NY: The Free Press.

Durkheim, E., & Lukes, S. (2013). *The rules of sociological method: And selected texts on sociology and its method* (Free Press trade paperback ed.). New York: Free Press.

Duwe, G. (2000). Body-count journalism: The presentation of mass murder in the news media. *Homicide Studies, 4,*364-399.

Duwe, G. (2004). The Patterns and Prevalence of mass murder in twentieth century America. *Justice Quarterly, 21*, 729-760.

Duwe, G. (2005). A circle of distortion: the social construction of mass murder in the United States. *Western Criminology Review, 6,* 79-78.

Duwe, G. (2007). Mass murder in the United States: A history. North Carolina: McFarland & Company, Inc.

Dyer, J. (1997). *Harvest of rage*. Boulder, CO: Westview Press.

Eliason, S. (2009). Murder-suicide: A review of the recent literature. *Journal of the American*
The Federal Bureau of Investigation. 2011. *Uniform Crimes Report.* Retrieved http://www.fbi.gov/about-us/cjis/ucr/crime-in-the-u.s/2011/crime-in-the-u.s.-2011

Ellison, C.G., Burr, J.A., & McCall, L.P. (2003). The enduring puzzle of Southern homicide: Is regional religious culture the missing piece? *Homicide Studies, 7,* 336-351.

Elkins, Z. & Simmons, B. (2005). On waves, clusters and diffusion: a conceptual framework. *Annals of the American Academy of Political and Social Science, 2,* 33-51.

Etzersdorfer, E., & Sonneck, G. (1998). Preventing suicide by influencing mass-media reporting. The Viennese experience 1980–1996. *Archives of Suicide Research, 4,* 67-74.

Ferguson, C. & Petherick, W. (2014). Getting away with murder: An examination of detected homicides staged as suicide. *Homicide Studies*, 1088767914553099.

Fox, J.A. (2013, November 25). Takeaways from the Sandy Hook Report. *Boston.com*. Retrieved from:http://www.boston.com/community/blogs/crime_punishment/2013/11/takeaways_from_the_sandy_hook.html

Fox, J. A. (2004). Missing data problems in the SHR imputing offender and relationship characteristics. Homicide Studies, 8(3), 214-254.

Fox J.A., & Levin J. (1998). Multiple homicide: Patterns of serial and mass murder. *Crime and Justice*, *23*, 407-445.

Fox J.A., & Levin J. (2003). Mass murder: An analysis of extreme violence. *Journal Applied Psychoanalytic Studies, 5*, 47–64.

Fox J.A., & Levin J. (2012). *Extreme killing: Understanding serial and mass murder.* Thousand Oaks, California: Sage Publications, Inc.

Fox, J. A., & Swatt, M. L. (2009). Multiple imputation of the supplementary homicide reports, 1976–2005. *Journal of Quantitative Criminology*, *25*(1), 51-77.

Gibbs, J. P. (1969). Marital status and suicide in the United States: A special test of the status integration theory." *American Journal of Sociology*, 74, 521-33.

Gibbs, J. P. (2000). Status integration and suicide: Occupational, marital, or both? *Social Forces*, *79*, 363-384.

Gillis, A.R. (1994). Literacy and the civilization of violence in the 19th century France. *Sociological Forum*, *9*, 371-401.

Girard, C. (1988). Church membership and suicide reconsidered: Comment on Breault. *American Journal of Sociology*, *93*, 1471-1479.

Geberth, V. (1996, February). The staged crime scene. Law and Order Magazine, *44*, 89-92.

Goldman, N. (1993). Marriage selection and mortality patterns: inferences and fallacies. *Demography*, *30*, 189-208.

Harper, D. W., & Voigt, L. (2007). Homicide Followed by Suicide An Integrated Theoretical Perspective. *Homicide Studies*, *11*(4), 295-318.

Hazelwood, R. & Napier, M. (2014). Crime scene staging and its detection. *International Journal of Offender Therapy and Comparative Criminology*, *48*, 744-759.

Hargarten, S.W., Karlson, T.A., O'Brien, M., Hancock, J., & Quebbeman, E. (1996). Characteristics of firearms involved in fatalities. Journal of the American Medical Association, 275, 42–45.

Henry, A. F., & Short, J. F. (1954). *Suicide and homicide: Some economic, sociological and psychological aspects of aggression* (Vol. 91442). New York: Free Press.

Hernández de Tubert, R. (2006, September). Social trauma: The pathogenic effects of untoward social conditions. In *International Forum of Psychoanalysis* (Vol. 15, No. 3, pp. 151-156). Taylor & Francis Group.

Hirschi, T. (1969). *Causes of Delinquency*. Berkeley: University of California Press.

Hirschi, T., & Stark, R. (1969). Hellfire and delinquency. *Social Problems*, *17*, 202-213.

Holmes, R. M. & Holmes, S.T. (1992). Understanding mass murder: A starting point. *Federal Probation*, *56*, 53-60.

Huff-Corzine, L., McCutcheon, J. C., Corzine, J., Jarvis, J. P., Tetzlaff-Bemiller, M. J., Weller, M., & Landon, M. (2013). Shooting for accuracy: comparing data sources on mass murder. *Homicide studies*, *8*, 105-124.

Jenkins, P. (1989). Serial murder in the United States 1900-1940: A historical perspective. *Journal of Criminal Justice, 17*, 377-392.

Johnson, B. D. (1965). Durkheim's one cause of suicide. *American Sociological Review*, *6*, 875-886.

Jones, B. S., & Branton, R. P. (2005). Beyond logit and probit: Cox duration models of single, repeating, and competing events for state policy adoption. *State Politics & Policy Quarterly*, *5*, 420-443.

Kelly, R. (2012). *Active shooter report: Recommendations and analysis for risk mitigation.* New York, NY: New York City Police Department.

Kessler, R. C., & Stipp, H. (1984). The impact of fictional television suicide stories on US fatalities: A replication. *American Journal of Sociology*, 151-167.

Kposowa, A. J., Breault, K. D., & Harrison, B. M. (1995). Reassessing the structural covariates of violent and property crimes in the USA: A county level analysis. *British Journal of Sociology*, *2*, 79-105.

Kowalski, G. S., & Duffield, D. (1990). The Impact of the Rural Population Component on Homicide Rates in the United States: A County-Level Analysis. *Rural Sociology*, *55*, 76-90.

Kurosu, S. (1991). Suicide in rural areas: The case of Japan 1960–1980. *Rural Sociology*, *56*, 603–618.

Ronald, J. (1988). Clustering of teenage suicides after television news stories about suicides: A reconsideration. *American Journal Psychiatry*, *145*, 1379-1383.

Fahey, S., & LaFree, G. (2015). Does Country-Level Social Disorganization Increase Terrorist Attacks?. *Terrorism and Political Violence*, *27*(1), 81-111.

Land, K.C., McCall, P.L., & Cohen, L.E. (1990). Structural covariates of homicide rates: Are there any invariances across time and social space. *American Journal of Sociology*, *95*,922-963.

Lankford, A. (2010). Do suicide terrorist exhibit clinically suicidal risk factors? A review of initial evidence and call for future research. *Aggression and Violent Behavior*, *15*, 334-340.

Lankford, A. (2013). A comparative analysis of suicide terrorists and rampage, workplace, and school shooters in the United States from 1990 to 2010. *Homicide Studies, 17*, 255-274.

Lankford, A. (2015). Mass shooters in the USA, 1966-2010: Differences between attackers who live and die. *Justice Quarterly, 32,* 360-379.

Laub, J. H., & Sampson, R. J. (1993). Turning points in the life course: Why change matters to the study of crime. *Criminology, 31*,301-325.

Lester, D. (1995). Explaining the regional variation of suicide and homicide. *Archives of Suicide Research, 1*, 159-174.

Lester, D. (1996). The regional variation of suicide in the United States in 1880 and 1980.*Omega, 34*, 81-84.

Levin, J., & Fox, J. A. (1985). Mass murder: America's growing menace (pp. 3-7). New York: Plenum Press.

Levin, J. & Madfis, E. 2009. Mass murder at school and cumulative strain: A sequential model. *American Behavior Scientist, 52*, 1227-1245.

Levitt, S. D. (1999). The limited role of changing age structure in explaining aggregate crime rates. *Criminology*, *37*, 581-598.

Loftin, C. (1986). The validity of robbery-murder classifications in Baltimore. Violence and Victims, 1(3), 191-204.

Maimon, D., & Kuhl, D. C. (2008). Social control and youth suicidality: situating Durkheim's ideas in a multilevel framework. *American Sociological Review*, *73*, 921-943.

Merton, R. K. (1938). Social structure and anomie. *American sociological review*, *3*, 672-682.
Marzuk, P. M., Tardiff, K., & Hirsch, C. S. (1992). The epidemiology of murder-suicide. *Jama*, *267*(23), 3179-3183.

Mazur, A. (1982). Bomb threats and the mass media: evidence for a theory of suggestion. *American Sociological Review*, *47*, 407-411.

McCauley, C., Moskalenko, S., and Van Son, B. (2013). Characteristics of lone-wolf offenders: a comparison of assassins and school attackers. *Perspectives on Terrorism*, *7*, 4-24.

McKnight, P. E., McKnight, K. M., Sidani, S., & Figueredo, A. J. (2007). *Missing data: A gentle introduction*. Guilford Press.

Maxwell, M. G. (1989). Circumstances in supplementary homicide reports. *Criminology*, *27*, 671-695.

Menninger, K. A. (1938). *Man against himself*. New York, NY: Harcourt, Brace & World.
Minnesota Population Center. (2011). *National Historical Geographic Information System: Version 2.0.* Minneapolis, MN: University of Minnesota.

Morgan, R. E., & Jasinski, J. L. (2016). Tracking Violence Using Structural-Level Characteristics in the Analysis of Domestic Violence in Chicago and the State of Illinois. *Crime & Delinquency*, 0011128715625082.

Mullen, P.E. (2004). The autogenic (self-generated) massacre. *Behavioral Sciences and the Law, 22*, 311-323.

O'Brien, R. M., & Stockard, J. (2006). A common explanation for the changing age distributions of suicide and homicide in the United States, 1930 to 2000. *Social Forces*, *84*, 1539-1557.

Osborne, J., Capellan, J.A. (*forthcoming*). Examining active shooter events through the rational choice perspective & crime script analysis. *Security Journal.*

Ostroff, R. B., Behrends, R. W., Lee, K., & Oliphant, J. (1985). Adolescent suicides modeled after television movie. *The American journal of psychiatry*, *142*, 989-989.

Palermo, G. B. (1997). The berserk syndrome: A review of mass murder. Aggression and violent behavior, 2(1), 1-8.

Petee, T.A., Padgett, K.G. & York, T. (1997). Debunking the stereotype: An examination of mass murder in public spaces. *Homicide Studies, 1*, 317-337.

Pizarro, J. M., & Zeoli, A. M. (2013). An assessment of the quality of homicide data in the Supplementary Homicide Reports: A research note. Justice Quarterly, 30(4), 711-731.

Phillips, D. P. (1974). The influence of suggestion on suicide: Substantive and theoretical implications of the Werther effect. *American Sociological Review,39*, 340-354.

Phillips, D. P. (1979). Suicide, motor vehicle fatalities, and the mass media: Evidence toward a theory of suggestion. *American Journal of Sociology*, *84*, 1150-1174.

Phillips, D. P. (1980a). Airplane accidents, murder, and the mass media: Towards a theory of imitation and suggestion. *Social Forces*, *58*, 1001-1024.

Phillips, D. P. (1980b). The deterrent effect of capital punishment: New evidence on an old controversy. *American Journal of Sociology, 86*,139-148.

Phillips, D. P. (1982). The impact of fictional television stories on US adult fatalities: new evidence on the effect of the mass media on violence. *American journal of sociology*, 1340-1359.

Phillips, D. P., & Hensley, J. E. (1984). When violence is rewarded or punished: The impact of mass media stories on homicide. *Journal of Communication*, *34*, 101-116.

Phillips, D. P., & Carstensen, L. L. (1988). The effect of suicide stories on various demographic groups, 1968–1985. *Suicide and Life-Threatening Behavior, 18*,100-114.

Pope, W. (1976). *Durkheim's Suicide: A Classic Reanalyzed*. Chicago: University of Chicago Press.

Porter, J. R., & Purser, C. W. (2010). Social disorganization, marriage, and reported crime: A spatial econometrics examination of family formation and criminal offending. *Journal of Criminal Justice*, *38*, 942-950.

Putnam, R. D. (1995). Bowling alone: America's declining social capital. *Journal of democracy*, *6*, 65-78.

Putnam, R. D. (2001). Bowling alone: The collapse and revival of American community. New York New York: Simon and Schuster.

Rafanell, I. Durkheim's social facts and the performative model: Reconsidering the objective nature of social phenomena. (2009). In G. Cooper (Ed.), *Sociological objects reconfigurations of social theory*. Farnham, England: Ashgate.

Recuenco, S., Eidson, M., Kulldorff, M., Johnson, G. & Cherry, B. (2007). Spatial and temporal patterns of enzootic raccoon rabies adjusted for multiple covariates. *Biomed Central, 6*, 1-15.

Regnerus, M. D. (2003). Moral communities and adolescent delinquency. *The Sociological Quarterly*, *44*, 523-554.

Rogers, E. (2003). *Diffusion of Innovations. 5th ed*. New York, N.Y.: Free Press.

Roman, R. (2003). Diffusion of innovations as a theoretical framework for telecenters. *Information Technologies & International Development*, *1*, 20-53.

Sampson, R. J., Laub, J. H., & Wimer, C. (2006). Does marriage reduce crime? A counterfactual approach to within-causal effects. *Criminology*, *44*, 465-508.

Sampson, R. J., & Laub, J. H. (1992). Crime and deviance in the life course.*Annual Review of Sociology*, *27*, 63-84.

Schwester, R. (Ed.). (2012). *Handbook of Critical Incident Analysis*. ME Sharpe.

Shaw, C. R., & McKay, H. D. (1942). *Juvenile delinquency and urban areas*. Chicago, Illinois: University of Chicago Press.

Schmidtke, A., & Häfner, H. (1988). The Werther effect after television films: new evidence for an old hypothesis. *Psychological medicine*, *18*(, 665-676.

Stark, R., Doyle, D. P., & Rushing, J. L. (1983). Beyond Durkheim: religion and suicide. *Journal for the Scientific Study of Religion*, *2*, 120-131.

Stack, S. (1980). The effects of marital dissolution on suicide. *Journal of Marriage and the Family*, *42*, 83-92.

Stack, S. (1982). Suicide: A decade review of the sociological literature. *Deviant Behavior*, *4*, 41-66.

Stack, S. (1988). The effect of domestic/religious individualism on suicide. The religion and family connection. *Social science perspectives, 3,* 175-204.

Stack, S. (1992). The effect of the media on suicide: The Great Depression. Suicide and Life-Threatening Behavior, 22(2), 255-267.Stack, S. (1993). The effect of modernization on suicide in Finland: 1800–1984. *Sociological Perspectives, 36*, 137-148.

Stack, S. (2000a). Suicide: a 15-year review of the sociological literature part II: modernization and social integration perspectives. *Suicide and Life-Threatening Behavior, 30,* 163-176.

Stockard, J., & O'Brien, R. M. (2002). Cohort effects on suicide rates: International variations. *American Sociological Review*, *67*, 854-872.

Simpson, M. E., & Conklin, G. H. (1989). Socioeconomic development, suicide and religion: A test of Durkheim's theory of religion and suicide. *Social Forces*, *67*, 945-964.

Tarde, G. (1903). *The Laws of Imitation*. Trans. Elsie Clews Parsons. 1stFrench ed., 1880; 2d ed., 1885. New York: Henry Holt.

Tolnay, S. E., Deane, G., & Beck, E. M. (1996). Vicarious violence: Spatial effects on southern lynchings, 1890-1919. *American Journal of Sociology*, 102, 788-815.

Turvey, B. (2000). Staged crime scenes: A preliminary study of 25 cases. Journal of Behavioral Profiling, *1*, 1-15.

Unnithan, P., Corzine, J., Huff-Corzine, L., & Whitt, H. (1994). *The currents of lethal violence: An integrated model of homicide and suicide*. NY: State University of New York Press.
Uggen, C. (2000). Work as a turning point in the life course of criminals: A duration model of age, employment, and recidivism. *American sociological review*, 67, 529-546.

Van Poppel, F., & Day, L. H. (1996). A Test of Durkheim's Theory of Suicide--Without Committing the" Ecological Fallacy". *American Sociological Review*, *61*, 500-507.

Wasserman, I. M. (1984). Imitation and suicide: A reexamination of the Werther effect. *American sociological review*, *18*, 427-436.

Wray, M., Colen, C., & Pescosolido, B. (2011). The sociology of suicide. *Annual Review of Sociology*, *37*, 505-528.

Wilcox, W., Dougherty, W., Fisher, H., Galston, W., Glenn, N., Gottman, J., et al. (2005).Why Marriage Matters, Second Edition: Twenty-Six Conclusions from the Social Sciences. *A Report from Family Scholars. Institute for American Values*: New York, NY.

Wooldredge, J., & Thistlewaite, A. (2003). Neighborhood Structure and Race-Specific Rates of Intimate Assault. *Criminology*, *41*, 393−422.

Yoshida, K., Mochizuki, Y., & Fukuyama, Y. (1991). Clustering of suicides under age 20--seasonal trends and the influence of newspaper reports. *Japanese journal of public health*, *38*, 324-332.

Zeger, S.L., & Liang, K.Y. Longitudinal data analysis for discrete and continuous outcomes. *Biometrics, 42,* 121-130.