Exploring the Structural Effects on the Lethal Violence at the U.S. Counties under the Situational Action Theory: An Application of Multivariable Spatial Regression Model

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EXPLORING THE STRUCTURAL EFFECTS ON THE LETHAL VIOLENCE AT THE U.S. COUNTIES UNDER THE SITUATIONAL ACTION THEORY: AN APPLICATION OF MULTIVARIABLE SPATIAL REGRESSION MODEL

by

YUNHO YEOM

A dissertation submitted to the Graduate Faculty in Criminal Justice in partial fulfillment of the requirements for the degree of Doctor of Philosophy, The City University of New York

2019
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Yunho Yeom

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.

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ABSTRACT

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by

Yun-Ho Yeom

Adviser: Jeremy R. Porter, Ph.D.

Since the stream analogy (Unnithan, Corzine, Huff-Corzine, & Whitt, 1994) and the frustration-aggression approach (Henry & Short, 1954) in lethal violence phenomenon analysis, several scholars have integrated theories from outside of their fields of study to understand lethal violence under a single theoretical framework. Some of these researchers have focused on deteriorating socioeconomic conditions and the collective attributional style when explaining the causes of lethal violence; others have failed to assume the non-independence of observation among contextual predictors. Recognizing these shortcomings, this study integrates the social components of situational action theory to examine their mediating effects on the relationship between socioeconomic context and lethal violence. At the same time, this study uses spatial analysis techniques to capture the spatial effect among the contextual predictors. These findings from the spatial analyses reveal that the geographical distribution of lethal violence in the U.S. counties is far from random; the spatial process needs to be considered in the aggregated analyses. This study also suggests that the social component indicators of situational action theory mediate the relationship between socioeconomic context and lethal violence.
ACKNOWLEDGEMENTS

I am deeply indebted to the members of my dissertation committee, Dr. Jeremy R. Porter, Dr. Hung-En Sung, and Dr. Kevin T. Wolff, who have guided me through this long journey. Their knowledge, wisdom, and insight have been invaluable. In addition, I would like to express sincere gratitude to my family who have unfailingly supported me throughout this journey. Lastly, I would like to acknowledge John Jay College of Criminal Justice and Graduate School, City University of New York for welcoming me into its excellent research environment.
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CHAPTER 1: INTRODUCTION

In 2014, the homicide rate per 100,000 people in the U.S. was 5.0; the comparable suicide rate was 13.4 (Kochanek, Murphy, Xu, & Tejada-Vera, 2016). Interestingly, the homicide rate slightly decreased from 6.1 in 1999 but the suicide rate had risen from 10.5. Consequently, the lethal violence rate, which is the sum of the homicide and suicide rates, increased from 16.6 in 1999 to 18.4 in 2014 (Gold, 1958; NVSS, 2017). This increase in the lethal violence rate has not only taken a heavy toll on human lives, but also posed “grave concern to both the public health and legal systems” (Wu, 2003, p. 215).

Furthermore, the two forms of lethal violence in the U.S. have not been evenly distributed, either spatially or temporally (Levi, 1982). In 2014, the state homicide rate ranged from 1.6 in Massachusetts to 14.7 in the District of Columbia. The suicide rate ranged from 7.9 in the District of Columbia to 24.5 in Montana. At the county level, these spatial discrepancies were more substantial. St. Louis County, Missouri, recorded a 36.9 homicide rate, seven times higher than the national average, 5.0. Lyon County, Nevada, recorded a 56.0 suicide rate; 2000 other counties recorded none (NVSS, 2017).

Several scholars have assumed that these spatial concentrations and variations in the homicide and suicide rates reflect a society’s contextual and structural features (Hooghe & Vanhoutte, 2011; James, 2014; Jorgensen, 2007; Lester, 1986; Levi, 1982; Messner, Anselin, Baller, Hawkins, Deane, & Tolnay, 1999; Pratt & Cullen, 2005). These features presumably influence the relationship between the homicide and suicide rates (Gold, 1958). According to Gold (1958), a higher suicide/homicide rate demonstrates that suicide is more likely to be chosen over homicide. These spatial variations in lethal violence phenomenon raise two questions: 1) why do the homicide, suicide, lethal violence, and suicide/homicide rates vary from one place to
2) what contextual and structural factors affect differences in the homicide rate, suicide rate, and lethal violence rate, and suicide/homicide rate?

There is a large body of research on the topic of these two forms of lethal violence with numerous theoretical frameworks and methodologies (e.g., Andersson, 2015; Baller, Shin, & Richardson, 2005; Batton, 1999; Browning, 2005; Jorgensen, 2007; Lester, 1987a, 1987b). Researchers have identified demographic or structural/cultural causes for the high suicide rate and the low homicide rate in the U.S. (Wu, 2003). Unfortunately, most researchers have examined the explanatory indicators of suicide and homicide separately, assuming that they are distinctive social phenomena (Wu, 2003). Fortunately, there have been several attempts to understand the relationship between the two under a single theoretical framework (Henry & Short, 1954; Unnithan et al., 1994).

For instance, the frustration-aggression approach posits that frustration within a society leads to aggression or violence, and that people who are frustrated express aggression either through suicide or homicide, depending on the external restraints (Henry & Short, 1954). These restraints are defined as “the degree to which behavior is required to conform to the demands and expectations” (Henry & Short, 1954, p. 120). Drawing upon the frustration-aggression approach, Unnithan et al. (1994) developed the stream analogy model, explaining that homicide and suicide are two competing channels within a single stream of lethal violence. Under this model, lethal violence is a product of two sets of causal mechanism: the forces of production and the forces of direction. The forces of production are “sources of frustration that affect the total amount of lethal violence.” The forces of direction “affect whether societal members are likely to attribute blame or responsibility externally” (Batton, 1999, p. 2; Unnithan et al., 1994).

The two approaches, frustration-aggression and stream analogy, maintain that a society’s
level of frustration (forces of production) determines its rate of lethal violence; attribution styles (forces of direction) motivate individuals to choose homicide over suicide, or vice versa (Unnithan et al., 1994; see also Tuttle, 2013). This collective preference for one type of violence over the other is reflected in the suicide/homicide rate (Gold, 1958). The two approaches have influenced subsequent suicide/homicide examinations and the literature. Some researchers have relied on these two sociological theories while others have incorporated theories from other fields (e.g., Andersson, 2015; Batton, 1999; Browning, 2005; Levi, 1982).

Several researchers have integrated these two theories, frustration-aggression and stream analogy, into strain theory, which assumes that frustration is the fundamental criminogenic factor. Strain theory is consistent with the two previous approaches (e.g., Andersson, 2015; Browning, 2005; Zhang & Lester, 2008). However, not all frustration leads to lethal violence, and not all homicides and suicides (e.g., suicidal terrorist attacks or altruistic suicides) are caused by frustration (Agnew, 2009; Bouhana & Wikström, 2011). In addition, these theories assume that attribution styles alone affect the structural/cultural factors that contribute to the rates of lethal violence and to suicide/homicide. However, attribution styles are not the only determinants. As strain theorists point out, not everyone who is frustrated resorts to violence if they have good coping skills (Agnew, 2009). Unlike the stream analogy and the frustration-aggression approach, situational action theory posits that violence is an interaction of individual propensity and criminogenic exposure, an interaction affected by perception-choice processes (Wikström, 2014). Under situational action theory, not everyone resorts to violence; people who refrain from violence have different morals and a different level of internal and external control, not different attribution styles.

Even though the perception-choice process is a satisfactory explanation of individual
variations in violence, “individuals do not act in an environmental vacuum” (Wikström & Treiber, 2007, p. 245), and behaviors are products of interaction between individual characteristics and contexts. Therefore, situational action theory posits and emphasizes that the perception-process is influenced by its context (Wikström & Sampson, 2003). Situational action theory notes the social contexts have multifaceted effects on individuals. For instance, moral education and cognitive nurturing influence the development of propensities for crime; a setting’s criminogeneity and moral context affect individuals’ perception-choice process (Wikström, 2014). Thus, personal choices need to be understood within the contexts in which individuals grow up and reside. Accordingly, Wikström and Sampson (2003) suggested that the nature and strength of community context influence “the individual development of propensity and motivation to offend;” thus, areas with weak community capital and collective efficacy are more likely to have “higher rates of children developing low self-control and weak morality” (pp.138-39).

The dual role of social context in situational action theory is parallel to the force of production and direction in the stream analogy. As the stream analogy posits that the contextual predictors concurrently determine both the lethal violence rate and suicide/homicide rate, situational action theory enables this study to assume that the dual role of context influences the lethal violence rate and suicide/homicide rate through the development of criminogenic settings and homicidal or suicidal propensity. As with the assumption of stream analogy approach that attribution styles have an impact on the structural/cultural effect on the lethal violence rate and suicide/homicide rate, situational action theory leads to the postulation that the contextual predictors developing collective morality and constraint affect the direct effect of contextual predictors on the lethal violence rate and suicide/homicide rate (e.g., Pratt, Turner, & Piquero,
2004; Schepers, 2017; Zimmerman, Botchkovar, Antonaccio, & Hughes, 2015). To clarify, this study does not focus on homicidal or suicidal propensity itself, but on the contextual predictors that influence that propensity. Therefore, by drawing on situational action theory, this study tests several contextual predictors and their mediating effects on the homicide rate, suicide rate, lethal violence rate, and suicide/homicide rate. The use of situational action theory is one of the essential contributions this study makes to the lethal violence studies even though some of variables in this study overlap with those of previous studies.

For instances, as proxies for the forces of production, researchers have included economic predictors, absolute and relative deprivation, to indicate the level of frustration that leads to lethal violence (Bills & Li, 2005; Chon, 2013; Lester, 1984, 1986). Absolute deprivation is captured with several economic indicators, such as the proportion of the population below poverty line, median income, infant mortality rate, and unemployment rate (Andersson, 2015; Batton, 1999; Browning, 2005; Dennis, 2010; Jorgensen, 2007; Tuttle, 2013; Wu, 2003). Relative deprivation is indicated by the use of economic Gini coefficients (Andersson, 2015; Chon, 2013; Dennis, 2010; Tuttle, 2013; Wu, 2003). In addition to economic indicators, social status or integration indices, such as the divorce rate (Jorgensen, 2007; Tuttle, 2013), percentage of single-parent households (Jorgensen, 2007), and ethnic/linguistic segregation (Batton, 1999; Dennis, 2010; Tuttle, 2013; Wu, 2003), have been used as proxies for the forces of production. With respect to the forces of direction, researchers have tested religiosity (Jorgensen, 2007; Tuttle, 2013), alcohol consumption (Batton, 1999; Jorgensen, 2007), divorce rate (Batton, 1999; Wu, 2003), ethnic/linguistic segregation (Batton, 1999), unemployment rate (Batton, 1999), and geographic region (Jorgensen, 2007), positing that the structural/cultural factors that affect attribution styles would lead to differences in the suicide/homicide rate (Vollum, 2001).
Some researchers assumed that a single contextual predictor, like the unemployment rate, is a source for forces of both production and direction, but others have suggested that different contextual predictors influence the two forces (Singh & Unnithan, 1999). Likewise, “the distinction between force of production and force of direction is not as clear empirically as claimed” (Wu, 2003, p. 217). Thus, depending on the theoretical framework, researchers have utilized the same predictor to examine different forces. Correspondingly, some variables used in previous studies are examined here. Variables, most of which are economic predictors, indicating the forces of production presumably affect the lethal violence rate in this study. In addition, other community variables, such as religiosity and alcohol consumption indicators, representing the forces of direction are assumed to affect the suicide/homicide rate, but with a different pathway, through mediation (Schepers, 2017). Thus, similar to the stream analogy, this study posits that the economic frustration predictors affect both types of lethal violence; however, the relationship would be affected through other contextual predictors (e.g., religiosity and alcohol consumption) that influence collective homicidal or suicidal propensity.

Moreover, even though most suicide/homicide studies under the original stream analogy and frustration-aggression models conceptualized suicide and homicide as a single social phenomenon, they focused on the relationship between contexts and only the lethal violence rate. Researchers have found that a single contextual predictor affects the forces of production and direction (Batton, 1999; Wu, 2003). In other words, a contextual indicator that is assumed to influence only the lethal violence rate has been found to influence homicide and suicide in different ways. It is therefore necessary to examine the contextual effects on homicide and suicide beyond the lethal violence rate and the suicide/homicide rate. Thus, in making a unique contribution to our understanding of these phenomena, this study expands the range of previous
theoretical perspectives through the integration of situational action theory to explain variations in the homicide rate and the suicide rate.

Methodologically, this study utilizes a geospatial analysis plan to examine and identify spatial processes operating to produce the between-county differences in the homicide, suicide, lethal violence and suicide/homicide rate in the U.S. while focusing on non-random spatial distributions and population characteristics that manifest as non-random spatial distributions. Most traditional studies on lethal violence have failed to consider “spatial dynamics arising from neighborhood interdependence” (Morenoff, Sampson, & Raudenbush, 2001, p.521). Contrary to the assumption of traditional studies, structural variables aggregated to the geographical units are statistically dependent (Townsley, 2009). Thus, several scholars have pointed out that ignoring the spatial effect among units might undermine the validity of inferential statistical models (Baller, Anselin, Messner, Deane, & Hawkins, 2001; Mears & Bhati, 2006; Morenoff et al., 2001, Tita & Radil, 2010). Thus, this study examines lethal violence with geospatial analysis to capture the spatial effect among geographic units.

In conclusion, this study complements what we know about the contextual explanations of lethal violence by explaining geographic differences in the homicide and suicide rates in U.S. counties based on situational action theory. It analyzes variations in the county-level homicide, suicide, lethal violence and suicide/homicide rates independently using indicators of frustration. These indicators are primarily economic, but include variables related to inequality, heterogeneity, and structural disruption. By testing the effect of the situational action theory model with this aggregate data, this study will develop contextual indicators that influence population-level characteristics affecting collective morality and constraint. These indicators include measures of religiosity and social controls, such as police presence. Ultimately, the
models in this study will take the form of a spatially weighted mediation model in which the contextual effects associated with aggregate levels of frustration on lethal violence will be examined as being influenced by the variation in the contextual predictors that influence the collective level of morality and constraint. The four models that examine four dependent variables, the homicide rate, suicide rate, lethal violence rate, and suicide/homicide rate, are included in figure 1.

**Figure 1. Conceptual Mediation Models**
CHAPTER 2: THEORETICAL FRAMEWORK

2.1. Suicide and Homicide as Social Phenomena

Researchers have attempted to identify structural/cultural or demographic factors for variations in the homicide and suicide rates under different theoretical frameworks and methodologies. For example, Baller et al. (2005) assumed that Sutherland’s concept of differential social organization could explain why learning processes that result in deviance are more likely to occur in a neighborhood endorsing deviant behaviors. Although researchers have applied different theories and methodologies, they have resulted in “a similar list of structural covariates to explain interunit variability in crime rates” (Land, McCall, & Cohen, 1990, p. 925).

However, most researchers have regarded the two forms of lethal violence as distinctive social phenomena; thus, they have rarely tested the two under a single theoretical framework (Wu, 2003; see also Quinney, 1965).

Nevertheless, the view of suicide and homicide as two independent social facts is a recent development; they have historically been considered a single phenomenon (e.g., Durkheim, 1897; Freud, 1957; Henry & Short, 1954; Unnithan et al., 1994). For instance, Durkheim (1897) maintained that the relationship between the two types of lethal violence might take different forms. Even though he did not argue that the same underlying forces influence the choices between the two forms of lethal violence, he noted that the two forms had either competing or opposed relations (Durkheim, 1897; see also Batton, 1999; Tuttle, 2013).

Taking a psychoanalytic perspective, Freud (1957) maintained that suicide and homicide cannot be different from each other due to their sources of aggression or frustration. Thus, “for Freud, suicide was simply the impulse to murder turned inward on oneself” (Batton, 1999, p. 21; see also Levi, 1982). These views on homicide and suicide were later conceptualized by the stream analogy and the frustration-aggression approach.
2.2. The Stream Analogy Approach

The stream analogy posits that homicide and suicide are competing channels within a single stream of violence (Unnithan et al., 1994). It notes that both suicide and homicide are a function of the forces of production and of direction. The two forces are influenced by what Merton (1938) called “anomie,” a disjunction between socially defined goals and legitimate means to attain them (see also Jorgensen, 2007; Unnithan et al., 1994). “Frustration is the first consequence of anomie;” thus, frustration is the major cause of the two forces (Unnithan et al., 1994, p. 20). Forces of production are “sources of frustration that affect the total amount of lethal violence”; in contrast, forces of direction are structural/cultural factors that “affect whether societal members are likely to attribute blame or responsibility externally” (Batton, 1999, p. 2; Unnithan et al., 1994). They argued that the contextual predictors, usually economic stressors and systemic frustration, affect the level of lethal violence within a society; structural/cultural factors affect the attribution styles, which lead to the variations in the suicide/homicide rate (Tuttle, 2013; Vollum, 2001).

Unnithan et al. (1994) emphasized attribution styles in their explanation of whether lethal violence is manifested in either homicide or suicide. They suggested that frustrated individuals are more likely to choose suicide over homicide when they blame themselves for their frustration. These attribution styles are influenced by structural/cultural predictors. This inward attribution style is most pronounced when frustrations are internal, stable, and global (Whitt, 1994). Individuals then tend to perceive themselves as helpless to control their frustration and to blame themselves (Whitt, 1994; Tuttle, 2013).

However, when individuals blame external circumstances for their frustrations, they are more likely to vent that frustration through homicide than through suicide. Individuals
externalize blame when they justify their frustration or failure as results of systemic unfairness (Cloward & Ohlin, 1960; Unnithan et al., 1994). Thus, under the stream analogy model, the prevailing attribution style within a society determines the direction of the lethal violence, as indicated by the suicide/homicide rate.

### 2.3. The Frustration-Aggression Approach

Based on frustration-aggression hypothesis, which posits that aggression originates from frustration (Dollard, Doob, Miller, Mowrer, & Sears, 1939), Henry and Short (1954) argued that the two types of lethal violence are results of same underlying cause: aggression, stemming from high levels of frustration. The original frustration-aggression hypothesis notes that criminality is a “function of the discrepancy between the absolute level of frustration and the absolute degree of anticipated punishment” (Andersson, 2015, p. 9). Henry and Short (1954) integrated the hypothesis in the explanation of lethal violence by expanding effects of economic factors on the levels of frustration. They hypothesized that fluctuations in the economy cause variations in hierarchical positions of individuals, and frustrations are closely related to aggression. They argued that when individuals experience “the loss of status position relative to others in the same status reference system,” they become frustrated and are more likely to get involved in lethal violence (Henry & Short, 1954, p. 56). Thus, they argued that economic environmental factors associating with frustration determine the rate of lethal violence within a society.

In a parallel with the argument of Unnithan et al. (1994), Henry and Short (1954) argued that even individuals experiencing similar levels of frustration express their aggressions differently. They argued that the likelihood of choosing suicide over homicide depends on the presence of external restraints, “the degree to which behavior is required to conform to the demands and expectations” (Henry & Short, 1954, p. 120). On the one hand, when external
Restraints are strong, frustrated individuals are less likely to die by suicide because they have others to blame. On the other hand, individuals surrounded by fewer external restraints, such as lack of family expectations, are more likely to die by suicide because they are not forced to conform to the expectations of others; thus, they have only themselves to blame. Consequently, Henry and Short (1954) argued that the attribution styles, affected by external constraints, determine the direction of aggression.

Although both Henry and Short (1954) and Unnithan et al. (1994) emphasized attribution styles in the explanation of variations in the suicide/homicide rate, the former noted that individuals’ status and the strength of the relational systems surrounding them are the major determinants whereas the latter pointed out that individuals’ subjective interpretation on the cause of frustrations are deciding factors for whether suicide is manifested over homicide, or vice versa. Despite these differences, the logical structure of frustration-aggression model is considered to be “identical to the concept of the stream analogy” (Batton, 1999, p. 26) because the frustration component in the model is parallel to the forces of production; the status and external constraint component is equivalent to the forces of direction in the stream analogy approach.

2.4. **Subsequent Integrated Models Based on the Two Approaches**

The stream analogy and the frustration-aggression models have substantially affected subsequent suicide/homicide researchers. Some of them have relied on these sociological frameworks only whereas others have expanded beyond sociology by integrating theories from other fields. For instance, some researchers have integrated strain theory, which assumes that frustration is the fundamental criminogenic factor and is consistent with the two previous approaches (Andersson, 2015; Browning, 2005; Zhang & Lester, 2008).
For instance, Browning (2005) combined two criminological theories, social disorganization and strain theory, with the stream analogy and the frustration-aggression models to account for the homicide rate and the suicide rate in Florida. Browning (2005) cited the main social disorganization and strain theorists and their research to explain homicide, not homicide and suicide. The study examined homicide under two criminological theories first and thereafter introduced the stream analogy and the frustration-aggression models to connect homicide with suicide as a flipside of homicide. The study examined the effects of structural covariates on two forms of lethal violence, but its focus remained at the associations between structural covariates and the homicide rate and the suicide rate only, not the lethal violence rate and suicide/homicide rate. In addition, the study noted its failure to consider spatial autocorrelation in the structural covariates; thus, it suggested for future study that using spatial multiple linear regression can “alleviate the problems associated with nonindependence of observations” (Browning, 2005, p. 76).

Moreover, pointing out the similarities between the frustration-aggression model and the general strain theory in criminology, Andersson (2015, p. 20) posited that “both frameworks argue that aggression or crime is the outcome of strains or frustration” and integrated the two perspectives to examine the cross-national homicide rate and suicide rate. Andersson (2015) relied on Agnew, Brezina, Wright, and Cullen (2002) who argued that “strains increase the likelihood that individuals will experience a range of negative emotion” (p. 44), which leads to criminal behavior. Drawing on strain theory, Andersson (2015) also argued that not all strained individuals get involved in the same type of lethal violence because individuals exert different cognitive, behavioral, emotional strategies to adapt to strain depending on personal traits, coping skills, social support, social control, or delinquent peers. Integration of the general strain theory
provides more narrowly defined causes not only for the lethal violence rate, but also for the variations of expressing strains or frustrations in either homicide or suicide, as indicated by the suicide/homicide rate. However, the study failed to consider spatial autocorrelation in the structural covariates and the outcome variables.

2.5. **Revisions to the Two Approaches**

Even though this study is aligned with the argument that both suicide and homicide are types of lethal violence. Suicide itself, as a distinctive concept from assisted suicide or euthanasia, is not a criminal act in most countries, including the U.S. (Adinkrah, 2012; Mendelson & Freckelton, 2013). Thus, suicide might not be less likely to be understood under a theory that explains criminal behaviors, such as social disorganization theory or strain theory. Also, as strain theorists themselves pointed out, not all frustration or strain leads to lethal violence, and all homicide or suicide is not caused by frustration or strain (Agnew, 2009; Bouhana & Wikström, 2011; Fox & Levin, 2003). For example, Fox and Levin (2003) suggested that homicides are motivated by several sources, such as a grudge against others (revenge killer), power and thirst to dominate (power killer), a warped sense of love (loyalty killer), satisfaction of needs (profit killer), and sending a message (terror killer).

Moreover, these approaches have focused on attribution styles when explaining differences in the choice of suicide over homicide, or vice versa. These approaches posit that whether blame for frustrations is directed against themselves or others is the major determinant for the choice. However, attribution styles are not the only determining factors, and frustrated individuals have another choice: abstaining from both type of lethal violence. As strain theorists themselves pointed out, not all frustrated individuals commit crimes because they sometimes possess coping skills (Agnew, 2009). Likewise, it is necessary to integrate theoretical
frameworks or predictors that can explain differences in the collective choice of suicide over homicide beyond attribution styles.

2.6. Integration of Situational Action Theory

Accordingly, this study expands the range of previous theoretical perspectives through integration of the situational action theory to explain variations in the homicide rate and the suicide rate in the U.S. counties. First, even though situational action theory intends to explain criminal behaviors, its definition on crime is inclusive and not normative. Therefore, it can explain suicide, which is not a criminal act per se. Under situational action theory, “crimes are acts that break rules of conduct stated in law,” but the law does not necessarily mean criminal codes (Wikström, 2014, p. 75). Wikström (2007) noted that “criminal law is set of moral rules, but not all moral rules are criminal law” (p. 347). Under situational action theory, a law is any rule that guides individuals on the right or wrong thing to do. Situational action theory focuses on the act of breaking, not on what is being broken. Thus, considering moral condemnation of suicide in almost every culture and society (Adinkrah, 2012), suicide can be understood as a crime under situational action theory because it is a rule-breaking behavior even though it is not criminally punishable.

Moreover, unlike the stream analogy and the frustration-aggression models, situational action theory posits that violence is an interaction of individual propensity and criminogenic exposure, and this interaction is affected by perception-choice process (Wikström, 2014). Situational action theory emphasizes the choice process by noting that individuals engage in lethal violence because they perceive and choose if “as an action alternative in response to a specific motivation” (Wikström, 2014, p. 75; Wikström & Sampson, 2003). However, the individual choice process is not the only causal mechanism in crime under situational action
theory. Individual selection is essentially a neighborhood effect embedded in higher-order structures (Sampson, 2013). In addition, studies have examined the associations among macro-level predictors, such as subculture of violence, demographic structures, and life-styles, and lethal violence (Land et al., 1990). Thus, situational action theory “aims to reconcile the role of deterministic and voluntaristic forces in the explanation of human action” (Wikström & Treiber, 2009, p.77). As a result, situational action theory addresses two separate components that determine violent behaviors: situational (the choice process) and social (Wikström, 2014). Even for the choice processes, the situational action theory emphasizes the setting, rather than the invariant characteristics of individuals.

2.6.1. The Situational Component

The situational component establishes “the casual mechanisms by linking individual and environmental factors” by explicating the situational factors that influence the perception process (Cochran, 2016, p. 812). According to Wikström (2014), the perception process is initiated by the two situational motivations: temptation and provocation. However, the two types of motivation under situational action theory are necessary, but not sufficient factors because individuals respond differently to similar motivation depending on their moral propensity (Cochran, 2016; Wikström, 2014). Under situational action theory, the moral propensity or morality is defined as “the rules that delineate what is right or wrong to do or not to do in a given situation” (Gallupe & Baron, 2014, p. 285). Individuals holding moral beliefs that are consistent with moral rules of the given situation are more likely to align their beliefs with surrounding rules and to exhibit shame or guilt when they violate the rules (Gallupe & Baron, 2014). Thus, individuals with strong morality are less likely to perceive violence as an action alternative when exposed to a certain motivation (Wikström, Ceccato, Hardie, & Treiber, 2010).
In addition to moral propensity, the perceived moral norms of setting encourage or discourage violence when the perceived norms are congruent or incongruent with individual morality. Conversely, when there is a conflicting rule-guidance, two types of control, internal- and external-control, impel individuals to comply with the moral norms of a setting. First, the situational action theory views self-control as a process “by which a person succeeds in adhering to a personal moral rule when it conflicts with the moral norms of the setting” (Wikström, Oberwittler, Treiber, & Hardie, 2012, p.26). Unlike the two prominent social control theorists, Gottfredson and Hirschi (1990), who viewed self-control as an individual trait, situational action theory views self-control is the product of individual executive capabilities and of setting (Wikström & Sampson, 2003; Wikström & Treiber, 2007). Such capabilities are not deterministic, but variant depending on “executive functions and training, and may be temporarily weakened by intoxication or high levels of emotion or stress” (Wikström, 2014, p. 82).

Second, the external control, deterrence, makes individuals comply with the moral norm of setting by reminding them of the “likelihood of getting caught and the associated sanctions for engaging in criminal/deviant behavior” (Cochran, 2016, p. 812). Even though external control influences individual compliance with moral norms, most individuals comply with the norms due to the guidance of their morality, not due to the fear of consequences of violation (Wikström, 2007). However, the two types of control are less likely to influence the perception-process of individuals with high or low morality because those individuals do not perceive deviance or non-deviance as an action alternative (Antonaccio & Tittle, 2008; Gallupe & Baron, 2014; Hirtenlehner & Hardie, 2016; Wikström, 2014; Wikström & Svensson, 2010).

Consequently, under situational action theory, individuals are more likely to engage in
lethal violence when they have moderate levels of morality, and internal- and external-controls fail to make them deliberately comply with the moral norms of setting. This indicates that individuals have different propensities for either homicide or suicide, and only individuals with a moderate moral propensity for either type consider them an action alternative. However, the propensity for violence is not deterministic, but variant depending on the community-level moral and cognitive vulnerability or attachment and social bonds (Bouhana & Wikström, 2011).

2.6.2. The Social Component

The situational component is an appropriate explanation of variations in lethal violence; however, its focus remains at the individual level. However, “individuals do not act in an environmental vacuum” (Wikström & Treiber, 2007, p. 245; see also Wikström & Sampson, 2003), and they socially and voluntarily construct their environments while social mechanisms reciprocally influence their development and action (Levi, 1982; Wikström & Sampson, 2003). Accordingly, lethal violence, not only as a result of individuals’ unacceptable choices, but also as a part of social pathology, has been assumed to be associated with society’s interpersonal interactions and structural disorders (Sampson, 2013). Situational action theory consequently posits that the individual development and action for violence interact with the broad social mechanism and context within a society (Wikström & Sampson, 2003; Wikström & Treiber, 2007).

Therefore, the interactions between an individual’s criminal propensity and the structural covariates have been examined (e.g., Gibson, 2012; Jones & Lynam, 2009; Lynam, Wikström, Caspi, Moffitt, Loeber, & Novak, 2000; Zimmerman, 2010), and the situational action theory is aligned with these empirical findings (Wikström & Loeber, 2000). For instance, expanding original social disorganization theory, Sampson and Groves (1989) argued that violence is
influenced by five types of contextual predictor: low SES, ethnic heterogeneity, residential mobility, family disruption, and urbanization. Likewise, as Durkheim (1897) argued, even though suicide is an individual choice, such a choice needs to be understood as deeply rooted in a broader social context (see also Sampson, 2013). Emphasizing the importance of contextual effects on violence, situational action theory integrates contextual components to explain the variations in violence in different neighborhoods.

Under situational action theory, a society sets its own rules or provides the resources that individuals draw upon. Individuals develop their future propensity to offend within that social context (Wikström & Sampson, 2003). Therefore, situational action theory emphasizes twofold effects of social contexts, social emergence and personal emergence. Personal emergence is sources of social context that affect individual crime propensity. On the one hand, Wikström (2014) noted that individuals develop their propensity for crime through distinctive psychosocial processes, such as moral education and cognitive nurturing provided by the society. On the other hand, the social emergence determines a setting’s criminogeneity and its moral context that imminently affect individual’s perception-choice process.

In particular, concerning social emergence, Wikström (2014) maintained that these contextual effects are not the cause of violence, but the “causes of the causes” (p. 83). Accordingly, Wikström (2014) notes that these twofold emergences explain how a society acquires “its particular mosaic of different kinds of human-made environments that provide particular opportunities and frictions in particular moral contexts” and “its particular mix of kinds of people with particular preferences, personal morals and abilities to exercise self-control” (p. 84). However, even affected by social contexts, individuals retain their free will. According to Wikström (2014, p. 84), depending on their preference, individuals can choose to “attend
particular time- and place-based activities within the constraints” of social forces.

Despite the possible exercise of individual free will, Wikström and Sampson (2003) emphasized that the community capital and collective efficacy affect community socialization processes of developing morality and self-control and the behavioral settings that lead to socialization. According to Wikström and Sampson (2003), community capital consists of the “resources and services (e.g., time, money, and knowledge) to support families”; collective efficacy includes parental support or community “capabilities to effectively monitor and react to rule violations outside” community (p. 131). The role of family and community in nurturing children is essential to predict the degree of morality and self-control within a society because the contextual effects on development of self-control or violent propensity are “likely to fade with age” (Wikström & Sampson, 2003, p. 133). Thus, the neighborhood with weak community capital and low collective efficacy is more likely to have a population with weak morality and low self-control (Sampson, 2011, 2013). These populations from socially disadvantaged neighborhoods have high levels of violence (Sampson, 2011, 2013).

Previous studies have examined the relationship between the neighborhood context and the level of control or morality in association with crime. These studies have usually conceptualized the control or morality as a situational concept that varies within different neighborhood contexts. For example, Sampson et al. (1997, p. 923) found that the low level of collective efficacy, indicated by the level of informal social control and social cohesion, “mediated substantial portion of the association of residential stability and disadvantage” with the level of violence. The study found that neighborhood contexts account for the neighborhood variation in collective efficacy, and collective efficacy, in turn, affect the association between neighborhood contexts and crime. Aligned with this study, research has found that the mediating
effects of collective efficacy or the level of social control on the relationship between neighborhood disadvantage and crime (Sampson, Morenoff, & Gannon-Rowley, 2002).

However, most studies of the mediating effects of control or morality have focused on the mediating effects of informal social control or subset of informal control, including collective efficacy, social ties and cohesion, and peer-group factors (Sampson et al., 2002). Few studies have examined the mediating effects of formal control or morality on the relationship between neighborhood context and crime. The studies that examined the mediating effects of formal control have usually conceptualized the formal control as police presence or police use of force (Krishan et al., 2014; Parker et al., 2005). For example, Terrill and Reisig (2003) found that police officers tend to use higher levels of force in disadvantaged neighborhood and those with higher homicide rates. The study suggested that “concentrated disadvantage and homicide rate are both linked to level of force” (Terrill & Reisig, 2003, p.303). Moreover, not many studies have explored the mediating effects of morality on such relationships because even though moral commitment was considered as an “important source of social control,” it has been a difficult to explain “what exactly constitutes one’s own moral values and belief” (Schoepfer & Piquero, 2006, p.55). Some studies that examined the mediating effects of morality conceptualized morality as willingness to comply with the rules of a setting. For instance, Simons and Burt (2011) found that individuals tend to develop a cognitive framework that views criminal actions as acceptable given prevailing adverse social-environmental conditions, and this crime-prone social schema is associated with the level of crime in socially disadvantaged areas.

Several studies took a different perspective by positing that the association between the level of control and crime is moderated by the neighborhood context (Jones & Lynam, 2009; Meier, Slutske, Arndt, & Cadoret, 2008; Zimmerman et al., 2015). Unlike the assumption of
situational action theory, these studies of the moderating effects of control or morality posited that the level of control or morality is “invariant across neighborhood contexts” (Meier et al., 2008, p.378). Even though these studies are based on different assumptions, they seemed to agree that the effects of control or morality on crime or exercise of control or morality are affected by the neighborhood context.

2.6.3. **Integration of Situational Action Theory into Suicide and Homicide Studies**

Accepting the assumption of situational action theory that individuals develop different levels of criminal propensity within social contexts, this study posits that individuals develop their own propensity for suicide or homicide. As the propensity for crime is defined as “the tendency to perceive and choose crime as an action alternative” under the situational action theory (Wikström & Svensson, 2010, p. 396), the propensity for suicide or homicide can be defined as tendency to perceive and choose suicide or homicide as an action alternative when exposed to the setting.

However, this perception-choice process at the individual level is not the focus of this study. Rather, aligned with the previous ecological studies and relying on the assumption of situational action theory on the contextual effects on human behaviors, this study assumes that homicidal or suicidal tendency or even preference for one over the other is determined by a broader social milieu in which individuals belong. In particular, consistent with previous studies under the stream analogy and the frustration-aggression approaches, this study posits that the economic environmental factors leading to frustration primarily impact the level of lethal violence by increasing the level of frustration. Additionally, this study examines the social component indices of situational action theory that influence individual perception with an assumption that the socio-structural features impact the contexts nurturing the morality and
control (Sampson, 2011, 2013). Thus, this study examines the mediating, not the moderating, effects of *contextual variables* that affect the level of morality and constraint because as situational action theory assumes, the neighborhood context affects not only the level of control and morality, but also that of crime or lethal violence.

2.7. **Spatial Dependence and Its Impacts on Suicide and Homicide Study**

In addition to integration of situational action theory, this study makes a methodological contribution to homicide and suicide studies by analyzing lethal violence with a spatially weighted statistical tool. Numerous studied have examined the ways in which different structural covariates impact lethal violence under different theoretical frameworks and methodologies (e.g., Hooghe & Vanhoutte, 2011; Jorgensen, 2007; Lee, Maume, & Ousey, 2003; Lester, 1986; Levi, 1982; Messner et al., 1999). However, most traditional studies have assumed the interdependence of neighborhoods and failed to consider “spatial dynamics arising from neighborhood interdependence” (Morenoff et al., 2001, p. 521). In other words, in traditional homicide and suicide studies, independent and dependent variables have been aggregated to geographical units and assumed to be statistically independent (Townsley, 2009).

However, as Townsley (2009) noted, covariates of crime and criminality are not in isolation; they influence each other. This interaction is engraved in the principal law of geography, “everything is related to everything else but near things are more related than distant things” (Tobler, 1970, p.236). In short, the interaction between two neighborhoods is affected by propinquity and can cause the characteristics of one neighborhood to spill over into adjacent ones (Messner et al., 1999). Stressing the importance of such spillover effect, several scholars have pointed out that the spatial process might undermine the validity of traditional inferential statistical models that ignore such spatial effect (Baller et al., 2006; Morenoff et al., 2001, Tita &
Moreover, as Morenoff et al. (2001) noted, the spatial effects on lethal violence are sometimes greater than those of structural covariates, and the neighborhood structural covariates are “severely constrained by the spatial context of adjacent neighborhoods” (p. 552).

Therefore, a growing number of studies in criminology has considered that the influence of structural conditions depends on or spills over to the spatially proximate neighborhoods (Baller et al., 2001; Mears & Bhati, 2006). These studies have found that violence or crime is not randomly distributed, but diffuses over space (Tita & Radil, 2010; Weisburd, Bruinsma, & Bernasco, 2009). Studies have found that the homicide rate and suicide rate in one neighborhood influence those in others (Baller & Richardson, 2002; Messner et al., 1999). Some scholars have described the spread of homicides and suicides among neighborhoods as “contagious” (Abrutyn & Mueller, 2014; Towers, Gomez-Lievano, Khan, Mubayi, & Castillo-Chavez, 2015). In the U.S., the contagious nature of lethal violence at the geographical level has been examined with different theoretical frameworks, methodologies, and units of analysis (Abrutyn & Mueller, 2014; Cohen & Tita, 1999; Haw, Hawton, Niedzwiedz, & Platt, 2013; Niedzwiedz, Haw, Hawton, & Platt, 2014; Ye & Wu, 2011). Homicide studies have found that the spatial distribution of the homicide rate in the U.S. at the different spatial unit is far from random (Mencken & Barnett, 1999; Messner et al., 1999). For example, utilizing the exploratory spatial data analysis (ESDA) technique, Messner et al. (1999) found that the county-level homicide rate in the St. Louis region was not randomly distributed, and local patterns of spatial autocorrelation moving from urban core toward adjacent counties were caused by a contagious diffusion process. Mencken and Barnett (1999) examined the county-level homicide rate in five southern U.S. states using ESDA, especially Moran’s I and G statistics, which are the two statistical indices of spatial dependence. They found that “many of
the predictors of murder and violent crime are spatially autocorrelated” and noted that ignoring spatial autocorrelation in the regression model causes its results potentially biased and inaccurate (Mencken & Barnett, 1999, p.418). The spatial clustering of homicide rate has been found in different geographical settings in the U.S. with different statistical methodologies (e.g., Cohen & Tita, 1999; Graif & Sampson, 2009; James & Cossman, 2006; Ye & Wu, 2011).

Similarly, in suicide studies, some scholars have explained that spatial clustering is caused by imitation or contagion that motivates individuals to share suicidal behaviors and beliefs (Tarde, 1903). Other scholars have noted that such clustering is caused by shared social characteristics within a certain geographic space that favor to the development of suicide (Durkheim, 1951). For example, Baller and Richardson (2002) compared these two conflicting views with spatial datasets of the U.S. and France and found that the spatial patterning of suicide rate is affected not only by the social imitation, but also by the shared social features, such as religious homogeneity. Similarly, utilizing geographically weighted regression models, Trgovac, Kedron, and Bagchi-Sen (2015) examined the effects of social isolation and fragmentation on the suicide rate in U.S. counties between 2000 and 2006. The study found that a spatial clustering of suicide rate across U.S. counties, and clustering varied by region, with Southern states having more negative coefficients for measures of social isolation than states elsewhere.

Likewise, the existence of spatial clustering in the suicide rate has been supported by previous meta-analyses (Haw et al., 2013; Niedzwiedz et al., 2014). For instance, after reviewing 82 studies, Niedzwiedz et al. (2014) found that suicide clustering occurs not only in specific institutional setting, such as psychiatric hospitals, schools, and prisons, but also in the general population and indigenous communities. Similarly, Haw et al. (2013) reviewed 46 studies and found that clustering might appear as masses or points. The study focused on point clustering,
which occurs in a small geographical area over a brief period, and explored underlying psychological mechanisms behind such clustering. The study did not focus on the structural covariates of suicide, but enumerated several socio-psychological causes of suicide, such as contagion, imitation, projective identification, and learning. The spatial clustering of suicide has been found in different regions of the U.S. with different statistical methodologies (e.g., Abrutyn & Mueller, 2014; Congdon, 2011; Phillips, 2013).

In conclusion, traditional studies on lethal violence have failed to consider the possible spatial autocorrelation among the phenomena themselves as well as structural covariates of lethal violence. The homicide and suicide rates are not randomly distributed at different geographic units, but spatially autocorrelated. Thus, assessing the presence of spatial autocorrelation in the datasets is a critical step in model specification to avoid potential biases (Tita & Radil, 2010). Accordingly, in addition to integration of the situational action theory model, this study applies spatial analysis to capture such spatial dependence or spillover in examining the structural covariates of lethal violence. These two substantive and methodological frameworks in combined are the essential contributions that this study makes in lethal violence research.
CHAPTER 3: IMPLICATIONS AND FINDINGS OF PREVIOUS STUDIES

Studies explaining variations in the homicide and suicide rates have assumed that the rates are associated with contextual and structural features of a society (Hooghe & Vanhoutte, 2011; Jorgensen, 2007; Lee et al., 2003; Lester, 1986; Levi, 1982; Messner et al., 1999; McCall, Land, & Parker, 2010). Aligning with this body of literature, this study examines the structural covariates of lethal violence under situational action theory. Unfortunately, there have been few studies of the structural covariates of lethal violence under situational action theory. Previous studies under situational action theory have focused on non-lethal crimes, such as juvenile delinquency (e.g., Lynam et al., 2000), academic dishonesty (e.g., Cochran, 2016), minor/violent offending (e.g., Gibson, 2012; Jones & Lynam, 2009), or drug use (e.g., Gallupe & Baron, 2014). Due to the lack of research on lethal violence under situational action theory, this study reviews previous research on non-lethal crimes.

Even these studies have operationalization issues due to the difficulties measuring the concepts of morality or self-control (Hitlin & Vaisey, 2013). In addition, except for the concept of external control, two other main concepts of the situational action theory, including morality and self-control, have been usually operationalized as individual traits, not as contextual characteristics (e.g., Gottfredson & Hirschi, 1990). However, situational action theory expands the meaning of self-control beyond individual traits. According to situational action theory, self-control is an interaction with settings (Wikström & Sampson, 2003; Wikström & Treiber, 2007). Based on this conceptual breakthrough, subsequent studies have posited that structural covariates influence the relationship between crimes and the several major concepts in the situational action theory, including morality, self-control, and external-control (deterrence) (Antonaccio & Tittle, 2008; Wikström & Svensson, 2010; Wikström & Treiber, 2007; Wikström & Treiber, 2017).
3.1. **Structural Covariates of Crimes under Situational Action Theory**

3.1.1. Morality

Morality is one of the main concepts of the situational action theory because individuals are less likely to commit a crime when they do not perceive the immoral behavior as an alternative (Wikström, 2014). The exercise of moral filtering is contingent upon the two factors, an individual’s endorsement of the moral rules and collective endorsement of moral rules by others participating in the setting (Wikström et al., 2012). For example, reviewing answers of 849 respondents in the Dhaka Districts of Bangladesh, Brauer and Tittle (2016) found that not only the strong moral belief and identity of individuals, but also strong enforcement of moral rules of setting, were negatively related to individuals’ contemplation of violence as an action alternative (see also Antonaccio & Tittle, 2008; Cochran, 2016; Tittle, Antonaccio, Botchkovar, & Kranidioti, 2010). They reasoned for such negative association that morality operates as an inhibitor preventing individuals from perceiving criminal behavior as an action alternative in the first place. Even though these studies have focused on the individual-level morality, they also emphasized that the morality is not fixed, but contextual or situational depending on surrounding settings (Brauer & Tittle, 2016; Cochran, 2016; Schepers, 2014).

Contextual studies have posited that morality reflects a society, and moral actions are dependent on social conditions and systems (e.g., Durkheim, (1973) [1925]; Hitlin & Vaisey, 2013; Hoffmann, 2015; Simons & Burt, 2011). This assumption is aligned with the situational action theory’s emphasis on the effects of community capital on the community socialization processes of developing morality and self-control (Wikström & Sampson, 2003). However, there have been few empirical studies exploring the effects of structural covariates on the relationship between morality and crimes. They usually focused on the association between the covariates
and morality itself, not in relation with crimes (e.g., Vauclair & Fischer, 2011). These studies have been based on cross-national analysis and assumed the structural level of religiosity as a main covariate of morality.

For example, Saroglou, Delpierre, and Dernelle (2004) conducted a meta-analysis on 21 studies and found that the level of religiosity was associated with the level of morality or the attitude toward societal value, but such association was attenuated in a nation with a higher SES (see also Roccas, 2005). Unfortunately, most studies, including Saroglou et al.’s (2004), failed to make a direct link between the contextual level of religiosity and criminal behaviors. However, Simons and Burt (2011) examined the effects of structural predictor, such as community crime and collective efficacy, on the internalized social schema, including cynical view of conventional norm. Even though the study did not directly measure the morality in general, it assumed that “disparaging view of conventional norms increases the probability of engaging in criminal behavior” (Simons & Burt, 2011, p. 560). They found that individuals tend to develop a cognitive framework viewing criminal actions more acceptable given prevailing adverse social-environmental conditions, including deviant peers, community crime, and lack of social ties. They argued that this crime-prone social schema is eventually associated with the level of crime in the socially disadvantaged areas.

3.1.2. Self-Control

Self-control has been historically considered as a major criminogenic factor; however, most studies view self-control as an individual trait. Gottfredson and Hirschi (1990) viewed self-control as a factor that is solely responsible for individual criminal behavior and that tends to persist across the life course. A low level of self-control increases violence because people who lack self-control are both perpetrators and victims of violence (Gibson, 2012; Schreck, 1999).
However, studies now assume that self-control is neither deterministic nor invariant. They contend that self-control is malleable; thus, appropriate and timely interventions or strong social bonds, such as stable employment and high-quality intimate relationship can redirect offenders into conformity (Na & Paternoster, 2012; Sampson & Laub, 1993). There is also evidence that self-control can be increased or decreased by other social sources, such as school socialization, religiosity, and adverse neighborhood conditions (e.g., Pirutinsky, 2014; Pratt, Turner, & Piquero, 2004, 2005).

Situational action theory reconceptualizes self-control as interacting with setting, not as an individual feature (Wikström & Treiber, 2007). Even though self-control is an individual trait, its exercise depends on a person’s executive capabilities and setting (Wikström & Treiber, 2007; see also Wikström & Sampson, 2003). Such capabilities depend on “executive functions and training, and may be temporarily weakened by intoxication or high levels of emotion or stress” (Wikström, 2014, p.82; see also Wikström & Svensson, 2008). With this reconceptualization, researchers have explored the effects of structural covariates on the relationship between self-control and crime (Burt, 2014). For example, using 1,431 randomly selected residents of 41 neighborhoods in Russia and Ukraine, Zimmerman et al. (2015) found that the association between the self-control and crime is influenced by ecological characteristics, such as neighborhood morality, but not by neighborhood SES or criminal opportunity. They also found that the association was strong in the neighborhood with the low level of morality. Zimmerman et al. (2015) reasoned that the exercise of self-control is contingent upon the context and deterrence characteristics of settings (see also Pratt et al., 2004; Wikström, 2010).

Similarly, Lynam et al. (2000) assumed that “interaction effects in which personal characteristics such as impulsivity would be more strongly related to offending in criminogenic
neighborhoods” (p. 564). Conducting both cross-sectional and longitudinal studies with a sample of teenagers in Pittsburgh, Lynam et al. (2000) found that the association between limited impulsivity or self-control and juvenile delinquency was strong only in the low-income neighborhood. They reasoned that the socially disadvantaged neighborhoods are characterized by low levels of informal social control, which increases the opportunity for crime and tempts juveniles with little self-control (Meier et al., 2008). This explanation is supported by their findings that “nonimpulsive boys in the poor neighborhood were no at greater risk for delinquency than nonimpulsive boys in better-off neighborhoods” (Lynam et al., 2000, p. 563). However, some researchers have found opposite (e.g., Zimmerman, 2010) or mixed (e.g., Gibson, 2012; Vazsonyi, Cleveland, & Wiebe, 2006; Wikström & Loeber, 2000) effects of neighborhood disadvantage on the relationship between self-control and crime.

3.1.3. External Control (Deterrence)

Situational action theory posits that as a situational mechanism, deterrence motivates individuals to comply with moral rules only when they perceive crime as an action alternative (Wikström, 2007). Thus, unlike studies under traditional deterrence theory, those based on situational action theory have explored the influence of deterrence in relation to morality beyond its independent influence on crime (Hirtenlehner & Hardie, 2016). With these assumptions, individual-level studies have produced consistent findings on the negative association between proxies for the level of deterrence and individual criminality (e.g., Grasmick & Green, 1981; Svensson, 2015; Wikström, Tseloni, & Karlis, 2011). In contrast, contextual-level studies have produced mixed findings on this association.

At the contextual level, researchers have posited that social and moral contexts affect the collective deterrence perception within a society, which leads to variations in crime rates (Apel,
Sanction publicity, police visibility, and sanction enforcement can be proper contextual-level predictors for deterrence perceptions (Apel, 2013); thus, studies have usually operationalized the predictors as number of police officers (e.g., Greenberg, Loftin, & Kessler, 1983; Lindström, 2013), police expenditure (e.g., Evans & Owens, 2007), or number of arrest and conviction (e.g., Kleck, Sever, Li, & Gertz, 2005). With these measures, some studies have examined how these structural covariates impact the individual deterrence perception whereas others have explored the association between the covariates and the crime rates within a society. Both approaches have produced mixed results (Cullen & Pratt, 2016).

Kleck et al. (2005) interviewed 1,500 adults in 54 large counties in the U.S. and found that the actual level of punishment, such as arrest and conviction rates, did not influence the level of perceived punishment. Similarly, Kleck and Barnes (2014) used the same sample in Kleck et al. (2005) and found that the number of police officers in a county did not influence the individual perceptions on the risk of arrest. However when examining the association between number of police officers or police expenditure and crime rate, studies have found negative (e.g., Evans & Owens, 2007; Lindström, 2013; see also Marvell & Moody, 1996), positive (e.g., Marvell & Moody, 1996), or null (e.g., Greenberg et al., 1983) effects.

3.2. Underlying Contextual Causes for Lethal Violence beyond Situational Action Theory

3.2.1. Religiosity

Several scholars have investigated the relationship between religiosity or religion and the level of violence under different theoretical backgrounds. On the one hand, the hellfire hypothesis posited by Hirschi and Stark (1969) notes that religion prevents violence “through the threats of supernatural sanctions and promotes normative behavior through the promise of supernatural reward” (Baier & Wright, 2001, p. 4). On the other hand, under the differential
association perspective, “religion affect peer selection such that individuals committed to
religion select peers with similar, conventional belief” (Baier & Wright, 2001, p. 5). Even though
each study’s theoretical assumptions and results have varied, religiosity operates as a protecting
factor against lethal violence (Andersson, 2015).

At the individual level, the relationship between religiosity and violence has been
explained in terms of the integrative and regulative roles of religion (Baier & Wright, 2001;
Pirutinsky, 2014). Under the integrative perspective, strong and effective bonds created among
members of the religious community are the sources of social capital that deter violent behaviors
(King & Furrow, 2004; Petts, 2009; Smith, 2003). In contrast, the regulative approach notes that
religion operates as a confounding or mediating factor for the relationship between self-control
and violence (Reisig, Wolfe, & Pratt, 2013). For example, Welch, Tittle, and Grasmick (2006)
noted that in competition with self-control, religiosity independently performs as a protecting
factor against violence whereas Pirutinsky (2014) argued that the religiosity decreases the level
of future violence partially mediated by the increased self-control. These two mechanisms have
been examined to prove the relationship between religiosity and violence at the individual level.

However, revisiting Durkheim’s concept of moral community, Stark (1984) suggested to
“stop treating religion only as an individual trait,” but to “seek its collective effects” because
religion is a social structure, and “individual commitment is energized by the group” (pp. 275-
281). Stark (1984) noted that religion is instrumental in enhancing social and moral integration,
which sustains the moral community where individuals tend to conform to the norms and attach
to each other. However, empirically, the relationship between religion and homicide has varied
depending on how to operationalize social context and religious ecology (Lee & Bartkowski,
2004a).
The first measurement approach assumes that religious participation, as a type of civic engagement, provides social capital or ties that deter criminal behavior (Lee & Bartkowski, 2004a; Messner, Baumer, & Rosenfeld, 2004; Putnam, 2000). Religious participation, regardless of denomination, is measured by the percentage of church membership or attendance, or the percentage of those who participate in church activities or those who volunteer for their place of worship (Messner et al., 2004; Putnam, 2000). For example, Lester (1987a, p. 685) found that “as a direct measure of the social integration,” the percentage of each state’s population attending church was negatively related to the homicide rate. In addition, using U.S. counties as units of analysis, Lee and Bartkowski (2004a) measured religious participation as two indicators, the proportion adhering to religious denomination and the number of churches per 100,000 people in the county and found that only the proportion adhering to religious denominations had significantly negative effects on the homicide rate. Moreover, Maume and Lee (2003) used the rate of adherence to be civically engaged religious denominations at the county level as a measure of noneconomic institution and found that the rate is negatively associated with the instrumental homicide rate, but not with the expressive homicide rate.

At the same time, the second approach operationalizes religiosity or religion based on the types of denomination. It posits that distinctive denominations have different effects on the homicide rate due to their own doctrines (Durkheim, 1951[1897]; Whitt, Gordon, & Hofley, 1972). This measurement approach posits that based on its own pedagogy and rituals, each denomination generates its own worldview that shapes its members’ political and economic views (Steensland, Park, Regnerus, Robinson, Wilcox, & Woodberry, 2000; Whitt et al., 1972). For example, Weber (1958 [1905]) argued that only ascetic Protestantism is consistent with modern urban-industrial values; thus, it is integrated with economic development. In contrast,
Catholicism is discordant with stimulating economic pursuits among its members. Thus, with this measurement approach, researchers have examined the different effects of each denomination on the homicide rate.

Wasserman (1978), using four southern U.S. states as units of analysis, found that the rate of Black Baptists in South Carolina were positively correlated with the homicide rate whereas the rate of White Protestants were negatively associated with the homicide rate in Alabama and Mississippi. In their comparison of the Evangelical Protestant, Mainline Protestant, and Catholic denominations, and the homicide rate at the county level, Beyerlein and Hipp (2005) found that the proportions of Mainline Protestant and Catholic adherents were negatively associated with the homicide rate; Evangelical Protestants were not. They reasoned that the two denominations encourage their believers to engage in the broader community activity beyond their own religious groups whereas Evangelical Protestant motivates its members to focus or volunteer in its congregation. Beyerlein and Hipp (2005) maintained that these differences on otherworldly pursuits differentiate bonding social capital, which eventually lead to different levels of HR. The positive relationship between the conservative religious denomination and the homicide rate has been supported by several researchers (e.g., Ellison, Burr, & McCall, 2003; Lee, 2006; Weaver, Martin, & Petee, 2004).

Likewise, relying on Durkheim’s theory on religion and the suicide rate, scholars have examined the contextual effects of religiosity on the suicide rate. Durkheim (1951[1897]) found that more Protestants died by suicide than believers of other religions and reasoned that Protestantism developed as a religion responding to “modern society by loosening its hold on members’ collective lives, thus forfeiting its ability to restrain self-destructive impulses” (Pescosolido & Georgianna, 1989, p.34). Like the homicide/religion researchers, most
researchers on suicide/religion relied on Durkheim’s view that religious affiliations are strong indicators of social integration and regulation, and their countering effects on suicides vary depending on the types of religion (Stack, 1983).

In accordance with the two operationalization approaches in the homicide studies, suicide studies have measured religion or religiosity based on either religious adherence or the proportion of different types of denomination. So when religion or religiosity was measured by religious adherence or participation, these rates had negative effects on the suicide rate or suicide ideology (e.g., Stack & Wasserman, 1995). For instance, Lester (1987a) found that the percentage of church attendance at the state level was negatively related to the suicide rate. Using the U.S. as units of analysis and time-series methodology, Stack (1983) found that the decline in the church attendance rates between 1954 and 1978 was negatively associated with the suicide rate during the same period. The negative association has been supported by several literatures (e.g., Bainbridge, 1989; Barkan, Rocque, & Houle, 2013; Stack & Wasserman, 1995).

On the other hands, when religion has been operationalized based on the types of denomination, the association between denominations, except Catholic, and the suicide rate has been relatively inconsistent depending on the geographical level and the number of denominations. For example, Phillips (2005) categorized denominations into three, Catholic, Episcopalian, and other Protestant, and found that only Episcopalian had a positive impact on the suicide rate at the state level over the time periods between 1976 and 2000 whereas Catholic had a negative impact only on the firearm suicide rate. In addition, Pescosolido and Georgianna (1989) categorized religion into 27 denominations and found Episcopalian had a positive effect on the county-level suicide rate whereas Catholic and Nazarene had negative impacts on the rate. In general, Catholic has had a relatively stable negative impact on the suicide rate in the different
spatial and temporal frames (e.g., Faupel, Kowalski, & Starr, 1987; Kowalski, Faupel, & Starr, 1987).

3.2.2. Alcohol Consumption Rate

Research has examined that the substantial proportion of violence incidences are associated with the intoxicated offenders and/or victims (Stack, 2000; Parker, Williams, McCaffree, Acensio, Browne, Strom, & Barrick, 2011). At the individual level explanation for the association, several researchers noted that the effect of intoxication decreases impulse control, limits ability to process information, and reduces anxiety about the consequence of violent behavior. In particular, intoxication weakens the operation of active constraint that prevents individuals from engaging in a violent behavior; thus, it reduces the possibility of employing non-violent conflict resolution alternative (Miles, 2012; Parker, 1995).

Nevertheless, a growing number of researchers have argued that “alcohol and drugs in isolation do not cause lethal violence,” but rather a complicated interaction of individual, situational, and social factors (Miles, 2012, p. 872). They have found that the effects of intoxication vary depending on the macro-level predictors (Parker et al., 2011). They have found that not only the per capita consumption per se relates to the homicide rate, but also its interaction with drinking patterns, a lack of social control, and divorce rates collectively increases the homicide rate (Miles, 2012). In particular, the majority of alcohol-violence studies focused on drinking culture and found that the association is stronger in the excessive drinking culture than in the moderate culture (Norström, 2011).

Moreover, the association between the alcohol consumption and the suicide rate has been well-documented (Batton, 1999; Sher, 2005; Stack, 2000). Ramstedt (2005) noted that most of studies examining the impact of contextual predictors on the suicide rate are based on time-
series analysis, and the per capita alcohol consumption is positively related to the suicide rate contingent on the drinking pattern of a society. Likewise, several studies have consistently found the positive association in the U.S. usually with time-series analysis techniques (e.g., Kerr, Subbaraman, & Ye, 2011; Landberg, 2009; Phillips, 2013). In these studies, the effects of alcohol on the suicide rate are parallel to those on the homicide rate in terms of that intoxication undermines the active constraint or the regulative controls of norms (Batton, 1999). However, unlike to homicide incidences where conflicts among individuals are essentially assumed, suicide incidences are more likely to be situations where preexisting suicidal thoughts are just realized by the “suicidal impulses that would have been controlled in a sober state” (Ramstedt, 2001, p. 60).

Likewise, the majority of studies have consistently found the contextual effect of intoxication on both homicide rate and suicide rate. However, they have rarely considered other contextual predictors beyond the drinking cultures. Some scholars argued that the association between alcohol and violence might be spurious or there might be, at least, other underlying factors for violence or alcohol consumption (Sher, 2005). For example, Sher (2005) argued that there have been some inconsistent results on the association between alcohol consumption and the suicide rate varying on time and locality, and these inconsistencies are assumed to result from failing to “a broad-based social characteristics related to social stress… associated with high rates of a variety of stress-related behaviors” (p.1012).

3.2.3. Presence of Police

Researchers have noted that the lack of capable of guardianship impacts violent behavior (e.g., Cohen & Felson, 1979). Also, Wikström (2014) argued that enforcement of rules by creating concern for motivated offenders, such as presence of police, makes them adhere to the
rules. On the other hands, Rose and Clear (1998) provided some evidence that overreliance on public controls, via police presence and incarceration, may diminish the capacity of informal controls in the community, which can result in more crimes. Even with these conflicting explanations on the effect of police presence, several homicide studies have assumed the deterring effect of police and found mixed results. For instance, reviewing 168 U.S. cities data in 1980 and 1990, Parker (2004) found that police presence, measured by the average number of police officers per 100,000 of the population, negatively impacted both Black and White homicide. On the other hands, Stansfield and Parker (2013) examined 168 U.S. cities data at three different time points, 1980, 1990, and 2000, and found that the number of sworn officers per 10,000 of the population positively impacted the homicide rate for White in all three time points and Black for only in 1990 (see also McCall et al., 2011). Other studies have found non-significant effects of police presence on the homicide rate with different units of analysis (e.g., Harer & Steffensmeier, 1992; MacDonald & Gover, 2005; McCall et al., 2008; Pyrooz, 2012).

3.2.4. Economic Predictors

Historically, several contextual predictors associated with economic conditions have been examined to identify their effects on lethal violence under different criminological theories, such as culture, strain, and social disorganization theory (Pridemore, 2002). Even though their theoretical frameworks are different to each other, these theories’ explanations for direct or indirect contextual causes for violence are usually related to the economic factors. In particular, homicide/suicide researchers relying on the strain theory viewed that the aggregate levels of frustration caused by economic hardship or changes in social status are associated with the elevated levels of lethal violence (Batton, 1999). Thus, several studies have found that locations or temporal periods with the higher proportion of population with economic hardship tend to
have the relatively higher lethal violence rate (e.g., Batton, 2004; Jones-Webb & Wall, 2008; Jorgensen, 2007; Lanier, 2010).

Moreover, since Blau and Blau (1982) and Messner (1982) who argued that the relative economic deprivation, rather than the absolute, is more strongly associated with the homicide rate, researchers have usually operationalized economic predictor as relative or/and absolute deprivation (Pridemore, 2002). However, there also has been a criticism that these operational distinctions “are not very distinct empirically” due to their substantial collinearity, evidenced by the fact that areas with “high (low) levels of absolute deprivation also tend to have high (low) levels of relative deprivation” (Land et al., 1990, p.944). Despite this criticism, it has been found that economic inequality predictors affect the homicide rate (Pratt & Cullen, 2005; see also Nivette, 2011).

3.2.4.1. Absolute Deprivation

Several theoretical traditions have maintained that the structural economic deprivation is associated with the lethal violence rates in the community by positing that the impoverishment contributes to low social ties, ineffective social control, or social disorganization (Pratt & Cullen, 2005; Pridemore, 2002). Subsequently, a substantial body of empirical research has repeatedly found a positive association between them (Batton, 1999). These findings have been relatively consistent only when research has measured the absolute economic deprivation as a collective measure that combines different economic indicators. In other words, when research examines the independent effect of each economic indicator, its effect becomes inconsistent depending on the unit of analysis, source of dataset, or statistical strategies (Batton, 2004; Chiricos, 1987, Kovandzic, Vieraitis, & Yeisley, 1998).

**Combined Indicator of Absolute Deprivation**
First, using combined measures of absolute deprivation, researchers have found a relatively consistent relationship between the poor economic conditions and the HR. Making distinctions from relative deprivation indices, researchers have usually combined the proportion living in poverty, the unemployment rate, the proportion of female-headed family, and the median income under a new predictor, concentrated poverty or resource deprivation (Lee, Hayes, & Thomas, 2008; Messner, et al., 2004). With these combined deprivation measures, researchers have repeatedly found the positive contextual effect on the homicide rate in the U.S. (e.g., DeFronzo & Hannon, 1998; Lee, 2006; Lee et al., 2003; McCall, Land, Dollar, & Parker, 2013; Wadsworth, 2010; Wang & Arnold, 2008; Whaley, Messner, & Veysey, 2013) whereas a few has found a null effect when combined with other variables (e.g., Harer & Steffensmmeier, 1992; Lee et al., 2008). Also, similar to the homicide studies, the relationship between the suicide rate and absolute deprivation have been found inconsistent in several studies, such as Kubrin and Wadsworth (2009) and Wadsworth, Kubrin, and Herting (2014) (positive), Nandi, Prescott, Cerdà, Vlahov, Tardiff, and Galea (2012) (negative), and Wadsworth and Kubrin (2007) (null effect).

**Unemployment Rates**

Moreover, when researchers operationalized the absolute deprivation with an independent economic indicator, they found mixed results depending on the proxies they choose to examine with (Chiricos, 1987; Hsieh & Pugh, 1993). First, the unemployment rates have produced inconsistent results. For example, using U.S. cities and states data in 1950, Land et al. (1990) found a positive effect of the unemployment rate on the homicide rate within cities, but a null effect within states. Also, using the county-level data between 1970 and 1999, Phillips (2006a) found that the unemployment rates were positively associated with the homicide rate.
across counties; however, the association became negative within counties over time. Likewise, some researchers found the positive association between them (e.g., McCall et al., 2013). Some researchers, however, have found a negative association (e.g., Stansfield & Parker, 2013) whereas some has found a null effect (e.g., DeFronzo & Hannon, 1998; Nalla & Alvarez, 2011). These inconsistent findings are supported by Chiricos (1987) who conducted a meta-analysis over 38 homicide studies and found a relatively weak association, as compared to the associations between the unemployment rate and other types of crime. Some researchers argued that these inconsistent findings are caused by the conflicting effects of unemployment on the criminogenic settings (Cantor & Land, 1985; Chiricos, 1987; Land et al., 1990). They argued that a higher unemployment rate increases motivated offenders while it also changes routine-activity patterns near the household that lead to less victimizations.

Similarly, scholars who examined the association between the unemployment rates and the suicide rate in the U.S. found inconsistent outcomes, but the majority has found relatively positive associations. For instance, examining the state-level panel data between 1979 and 2010, Defina and Hannon (2015) found that the unemployment rate on the suicide rate varied contingent upon the time periods. They found a significant effect for pre-1995 period, but not for the post-1995. Similarly, Kowalski et al. (1987) found that the unemployment rates positively impacted the suicide rate in the most-urban counties, but negatively impacted it in middle-urban counties. Likewise, researchers have found the positive effect of unemployment on the suicide rate with different datasets (e.g., Chang & Chen, 2017; Faupel et al., 1987; Minoiu & Andrés, 2008; Phillips & Nugent, 2014; Recker & Moore, 2016). Only a few studies have found a null or mixed effect (e.g., Kerr, Kaplan, Huguet, Caetano, Giesbrecht, & McFarland, 2017; Nalla & Alvarez, 2011; Phillips, 2013; Trgovac et al., 2015).
Below Poverty Line

In addition, researchers have examined the effects of the proportion of population below poverty line as a proxy for absolute deprivation (Hsieh & Pugh, 1993; Pridemore, 2002). Similar to other economic indicators, the below poverty line index has produced mixed effects, but has had relatively stable and consistently positive effects on lethal violence (e.g., Messner & Tardiff, 1986; Stansfield & Parker, 2013; Weaver et al., 2004). Still, some researchers have found a null effect (Schacht, Tharp, & Smith, 2016); a few found a negative effect on the homicide rate (Messner, 1982). These strong positive associations have been supported by some meta-analyses (Hsieh & Pugh, 1993; Pridemore, 2002). For instance, after reviewing 34 studies, Hsieh and Pugh (1993) found that “combined estimate of association for poverty and homicide is significantly larger than” (p. 195) other violent crimes, but their coefficients fluctuated based on the geographical level. Similarly, Pridemore (2002) found that among 71 models reviewed, only five produced negative effects; the remaining models produce either positive or null effects. Few studies have examined the independent effect of below-poverty line indices on the suicide rate, but the associations have been generally positive (e.g., Kerr et al., 2017; Moore, Recker, & Heirigs, 2014; Recker & Moore, 2016).

3.2.4.2 Relative Deprivation

Researchers have posited that relative deprivation has a more positive impact on the homicide rate than does absolute deprivation (Batton, 1999). They assume that relative deprivation generates a sense of resentment and hostility, which manifests in aggressive impulses and violent crimes (Messner, 1989; Messner & Tardiff, 1986). In addition, a body of empirical research has found that the effect of relative deprivation is independent from that of absolute deprivation (Kovandzic et al., 1998). With these assumptions, researchers in the U.S. have
examined the contextual effects of economic inequality on the homicide rate with different theoretical frameworks, methodologies, and units of analysis (Pratt & Cullen, 2005; see also James & Cossman, 2006; James & Porter, 2012).

Using spatial regression models, Wang and Arnold (2008) examined the effects of income inequality on the homicide rate in the city of Chicago with three units of analysis: census track, neighborhood clusters, and community areas. The study found that relative deprivation was positively related to the homicide rate, and that the association was larger when the unit was smaller. They reasoned that “the perception of inequality is mainly derived from individuals’ familiarity within a local area” due to their “limited spatial range of mental map” (Arnold & Wang, 2008, p. 268). This reasoning is congruent with the assumption of relative deprivation that individuals become more hostile and aggressive when they perceive themselves deprived only in relation to perceptible reference groups (Messner, 1982; Messner & Tardiff, 1986; Pridemore, 2002). However, contrary to these findings, some scholars suggested that “inequality analyses ought to be conducted at relatively large geographical scale” (Whitworth, 2011, p.726). Despite controversies over the appropriate unit of analysis, several researchers found the positive contextual effect of relative deprivation on the homicide rate in the U.S. (e.g., Harer & Steffensmmeier, 1992; McCall et al., 2013; Mellor & Milyo, 2001; Roberts & Willits, 2015; Stansfield & Parker, 2013; Weaver et al., 2004). In particular, Harer and Steffensmmeier (1992) examined not only the Gini coefficients as proxies for relative deprivation, but also between-or within-race inequality measure.

Using different geographic units in the U.S., some researchers have found negative (Kposowa, Breault, & Harrison, 1995) or null (e.g., Lanier, 2010; Messner, 1983; Messner & Tardiff, 1986) effects of inequality predictors on the homicide rate. These inconsistent findings
are supported by several meta-analyses on the relationship between the homicide rate and social context (Hsieh and Pugh, 1993; Pridemore, 2002). For instance, reviewing 71 models of studies between 1969 and 1990, Pridemore (2002) found that the contextual effects of inequality on the homicide rate in the U.S. were mixed. 29 reported positive; five showed negative; and 37 indicated null effects. Reasons for the inconsistent findings include “disparate samples, multicollinearity, improper measures of inequality, incorrect level of analyses…” (Pridemore, 2002, p. 137). These inconsistencies are also found in the cross-national homicide studies (Nivette, 2011).

Similarly, there are many studies of the relationship between economic inequality and the suicide rate in the U.S. Similar to the reasoning for the association between the inequality indicator and the homicide rate, researchers have posited that “inequality may increase suicide by increasing the prevalence of strain, resentment, and alienation within the community” (Wadsworth & Kubrin, 2007, p. 1859). With these assumptions, researchers have tested the association between economic inequality and the suicide rate; however, their findings have been inconsistent depending on the geographical units, races, and genders. For example, using counties as units of analysis, both Kowalski et al. (1987) and Faupel et al. (1987) found that income inequality, indicated by the Gini coefficients, increased the suicide rate within the middle and most urban counties, but not the least urban counties. Similarly, Wadsworth and Kubrin (2007) examined the metropolitan statistical areas and found that the higher level of White/Hispanic economic inequality indicator, which represents the relative economic deprivation between White and Hispanic, leads to more suicides among Hispanics. Mellor and Milyo (2001) found the suicide rate at the state level was negatively associated with the Gini coefficients. Some studies, however, have found no significant association (e.g., Kubrin &
Wadsworth, 2009; Miller, Piper, Ahern, Tracy, Tardiff, Vlahov, & Galea, 2005; Minoiu & Andrés, 2008).

3.2.5. Family Disruption

As a contextual factor of concentrated disadvantage, family disruption has been examined in relation to lethal violence under several theoretical traditions (Pratt & Cullen, 2005). Several indicators have captured family disruption—the percentage of divorced or separated, single-headed households, and female-headed households—but researchers have often used the divorce rate or the marriage rate to indicate the degree of social cohesion or marital stability (e.g., Moore et al., 2014; Stack & Wasserman, 1995).

Researchers have found a positive association between the divorce rate and the homicide rate (Pridemore, 2002). For example, Stansfield and Parker (2013) found that the male divorce rate indiscriminately and positively affected the homicide rate of Black and White males. Similarly, examining 208 cities in the U.S., Whaley et al. (2013) found that the divorce rate indistinctively had positive impacts on the inter- and intra-sexual homicide rate. After reviewing 214 empirical studies between 1960 and 1999, Pratt and Cullen (2005) argued that the high rate of family disruption is one of “the strongest and most stable predictors of crime” (p.425). Likewise, a substantial body of research has identified the positive effects of the divorce rate on the homicide rate at different geographic unit of analysis in the U.S. (e.g., Lee et al., 2003; McCall et al., 2013; Messner & Tardiff, 1986; Phillips, 2006a; Stansfield & Parker; Wadsworth, 2010). Researchers have rarely found a positive effect divorce rate on the homicide rate; some have found a null effect (e.g., DeFronzo & Hannon, 1998; Messner et al., 2004). For example, Pridemore (2002) reviewed 45 models that included the divorce rate as a contextual predictor of social ties and found that 33 models produced positive effects; 12 produced null effects whereas
none of models had a negative effect on the homicide rate. Some scholars argued that the consistent and strong effects of the divorce rate on the homicide rate might originate from the reciprocal causal relations with other homicide predictors, such as poverty, unemployment, or other low SES indicator (Messner & Tardiff, 1986).

Moreover, research has found that the high divorce rate is positively associated with the high suicide rate in the U.S. The rationale behind this association can be traced to Durkheim. Durkheim (1897) found that the suicide rate was higher in males than females, higher for people without children than with children, and higher for people who are single than those who are in a relationship. He used these findings to argue that rapid social changes cause the breakup of social solidarity, thereby making people more vulnerable to suicide. Later researchers have found that the divorce rate, as a proxy for deterioration of social solidarity, is positively associated with the suicide rate. For instance, reviewing the county-level suicide rate in relation to several contextual predictors, Recker and Moore (2016) found that a county’s divorce rate had a positive association with other SES predictors. They reasoned that the higher divorce rate indicated less social support, which is closely related to the suicide rate.

Some researchers have tested the effects of divorce rate on the suicide rate in relation to other contextual proxies for social solidarity, such as church attendance or religious activities (e.g., Bainbridge, 1989; Faupel et al., 1987; Stack & Wasserman, 1995). Some of them found that religion had a stronger suicide-reducing effect than marriage; others suggested that religion has an indirect effect on the divorce rate. However, all researchers found an independent positive effect of the divorce rate on the suicide rate. Likewise, a substantial body of empirical research has found that the positive effect of divorce rate on the suicide rate survives in consideration with other SES or structural variables (e.g., Cutright & Fernquist, 2005; Minoiu & Andrés, 2008;
Moore et al., 2014; Phillips & Nugent; Wadsworth & Kubrin, 2007).

3.2.6. Age Structure

The association between individuals’ age and criminal propensity has been repeatedly supported by numerous researchers (e.g., Gottfredson & Hirschi, 1990; Phillips, 2006b). These consistent findings suggest that young people are more likely to be exposed to criminal opportunities and motivation (Cohen & Land, 1987; MacDonald & Gover, 2005; O’Brien & Stockard, 2002). Relying on these findings, subsequent researchers have posited that as criminal opportunities and motivations differ by time and location, “the pattern of age-specific homicide rates may be affected by and the effect of age structure on crime rates should fluctuate accordingly” (Phillips, 2006b, p. 234; see also Cohen, Llorente, & Eisdorfer, 1998).

Nevertheless, their findings depend on the units of analysis and datasets (Marvell & Moody, 1991; Phillips, 2006b). Some studies have found that rate of young population positively impact the homicide rate (e.g., Lee et al., 2008; McCall et al., 2013; Phillips, 2006b) whereas others have found negative (e.g., DeFronzo & Hannon, 1998; Krivo & Peterson, 2000, Lee & Bartkowski, 2004a; Lee et al., 2003) or null effects (e.g., Kovandzic et al., 1998; Lee & Bartkowski, 2004b; Messner & Tardiff, 1986). Reviewing 62 research models that used either cross-sectional regression or time-series method, Marvell and Moody (1991) found that 38 models produced positive associations between young populations and the homicide rate; 14 indicated negative associations; and nine showed mixed or null effects. They reasoned that these inconsistencies contributed to wrongly chosen age structure, other confounding or intervening factors influencing the homicide rate, or inherent problems with the compilation of data.

In contrast to the homicide studies, a series of suicide studies has focused on elderly populations that are supposedly more susceptible to suicide (Lester, 1987b). Researchers have
posited that despite variations in the suicide rate for different age groups, this difference does not merely originate from age itself, but other age-specific issues, such as economic and relational frustration, which individuals inevitably experience (Bainbridge, 1989; Phillips & Nugent, 2014). Using the median age within different geographic levels, several studies have found positive relations between the median age and the suicide rate (e.g., Gove & Hughes, 1980; Moore et al., 2014; Recker & Moore, 2016) but not many studies have found the negative effects of age on the suicide rate (Faupel et al., 1987). Bainbridge (1989) used the percentage of the population aged 65 and over as a control variable and found that age was “the best predictor” (p. 293) among other contextual predictors, such as church attendance or the divorce rate. Gove and Hughes (1980) reasoned that being older is closely related to a lifestyle that includes living alone and heavy alcohol consumption.

3.2.7. Gender Ratio

Several theoretical traditions have noted that males are more likely to engage in violent behaviors, not because of their gender, but because of their responses to socioeconomic disadvantage or loss of status (Bourgeois, 2003 [1996]; Phillips, 2006b). When in a setting that places them at a disadvantage, males are more likely to demonstrate their masculinity. At the contextual level, the size of the male population (percentage male or gender ratio) across time and place has been considered to affect the level of lethal violence. However, most studies have focused on gender in the homicide or suicide rate; thus, there have been few studies of the contextual effects of gender on the homicide or suicide rate.

Within these studies, the effects of gender ratio on the homicide rate have depended on the unit of analysis and period. For instance, using county-level annual data between 1970 and 1999, Phillips (2006b) found that the percentage of males in counties was positively associated
with the high level of homicide. In contrast, McCall et al. (2013) examined data of 150 U.S. cities at three points in time and found that the gender ratio in 1980 and 1990, but not in 2000, had a significantly negative impact on the homicide rate. Using 159 city datasets for youth-on-youth homicide rate, MacDonald and Gover (2005) found that the male ratio did not have a significant effect on the homicide rate (see also Lee et al., 2003; Parker, 2004). For the association between the gender ratio and the suicide rate, Phillips and Nugent (2014) considered the percentage of male population aged 65 and over and the percentage of male as control variables and found that both predictors were positively associated with the suicide rate at the state level between 1997 and 2000.

3.2.8. Ethnic Heterogeneity

Under conventional criminological theories, some researchers have noted that “immigration may increase violence by destabilizing communities and contributing to structural sources of violence” (Feld Meyer, 2009, p. 781; see also Shaw & McKay, 1942). However, more researchers, relying on immigrant-assimilation assumption, have posited that “immigration may stabilize communities and reduce violence by providing protective community resources and strengthening social institutions and social capital networks” (Feldmeyer, 2009, p.781; see also Davis & Fagan, 2012; Lee, Martinez, & Rosenfeld, 2001). Thus, there has been a series of empirical studies examining the association between the ethnic heterogeneity and crime under the two different theoretical approaches. They have usually measured the level of heterogeneity with the percentage of specific racial population or the percentage of immigrant regardless of their race.

First, researchers have examined the association between the percentage of specific racial group and the HR. They have found mixed results depending on different racial groups or
the unit of analysis. For example, using the percentage of Black, researchers found positive associations between the percentage of Black and the homicide rate at different units of analysis, such as U.S. cities over 100,000 (e.g., Kovandzic et al., 1998; Krivo & Peterson, 2000; Messner, 1982) and counties (e.g., Lee & Bartkowski, 2004b; Phillips, 2006b). Examining U.S. city data between 1980 and 1990, Parker (2004) found that the concentration of the Black population was negatively associated with the homicide rate of different races and genders (see also Lee, 2006). In addition, studies have focused on other racial groups, such as Hispanic or Latino populations, and examined their population effects on the homicide rate. Some researchers have found positive associations (e.g., Stansfield & Parker, 2013; Wang & Arnold, 2008) whereas others have found null effects of Hispanic populations (e.g., MacDonald & Gover, 2005; McCall et al., 2008).

Conversely, some studies have not targeted specific racial groups, but examined the aggregated percentage of all immigrants or ethnic groups. When they used these aggregated variables, researchers have found mixed effects. For example, Wadsworth (2010) used several heterogeneity indicators, such as the percentage of Blacks and Latinos, the percentage of foreign-born, and the percentage of new immigrants who arrived in the five years preceding the study. Applying OLS regression, Wadsworth (2010) found that only the percentage of Black and foreign-born populations had positive effects on the homicide rate in the 459 U.S. cities in 1990. In the same study, using time series analysis, Wadsworth (2010) found that the percentage of Blacks remained significant whereas the foreign-born effects become null, and the percentage of new immigrants negatively impacted the homicide rate between 1990 and 2000 (see also Nielson & Martinez, 2009). Similarly, Chavez and Griffiths (2009) made a distinction between foreign-born and recent immigrants, and found that the growth in the foreign-born population was
unrelated to the homicide rate; the increase in recent immigrants was associated with the lowest levels of violence in Chicago between 1980 and 1995. These studies show that the new immigrants are not necessarily predisposed to crime; instead, they are more likely to be highly motivated to succeed and to be law-abiding (Wadsworth, 2010).

Likewise, positing the contextual effects of heterogeneity on the suicide rate, researchers have examined the association between ethnic diversity and the suicide rate. A substantial number of researchers have found negative associations between the percentage of racial minorities and the suicide rate with different units of analysis and methodologies. For example, using the average suicide rate between 1999 and 2009 at the county level, Recker and Moore (2016) found that a large non-White population was positively related to the suicide rate within states. They explained that the non-White groups are more likely to provide social support and make connections among groups. By the same token, some researchers have found the negative effects of ethnic heterogeneity using the different unit of analysis, such as cities (e.g., Gove & Hughes, 1980), counties (e.g., Faupel et al., 1987; Moore et al., 2014), and states (e.g., Phillips & Nugent, 2014). Some researchers have found null effects (e.g., Nalla & Alvarez, 1995; Wadsworth et al., 2013).
CHAPTER 4: RESEARCH QUESTIONS

Based on the stream analogy and the frustration-aggression approach, this study zooms in on the uneven spatial variations of the homicide rate, suicide rate, lethal violence rate, and suicide/homicide rate at the U.S. county level and on how the structural covariates contribute to such variations. In particular, as traditional studies under the two approaches have found, this study assumes that socioeconomic frustrations primarily and substantially affect lethal violence within the U.S. counties. Thus, this study examines the effect of structural socioeconomic predictors on each dependent variable while controlling other non-socioeconomic predictors.

In addition, the social components of situational action theory that explain contextual effects on the morality and criminal propensity are important aspects of this study. Situational action theory explains that personal emergence is a source of social contexts that affect criminal propensity; thus, the neighborhood with weak community capital and ties would have low level of collective morality and constraint. Therefore, as previous researchers have pointed out, this study assumes that the collective level of morality and social constraints within each county would affect the level of lethal violence. In this study, collective morality is defined as a level of moral belief that distinguishes right from wrong in and collective willingness or tendency to align their beliefs with surrounding rules. The social constraint is defined as a formal or informal control at the contextual level that motivates individuals to comply with moral beliefs. These concepts are not directly operationalized with specific contextual-level indices, but with proxy variables that have been found to impact the level of morality and constraints in the previous studies. These proxy variables include rates of population for different religious denomination, alcohol consumption level, and number of police officers within counties. In particular, this study ultimately aims to examine the effects of these situational action theory’s social component indicators mediate the direct relationship between socioeconomic covariates and the lethal
violence.

Methodologically, as several scholars have found non-random spatial distribution of lethal violence and its covariates, this study assumes the non-independence of observation in contextual predictors and outcome variables. Consistent with previous studies, this study assumes the presence of spatial autocorrelation among contextual predictors to avoid potential bias in model specification. Thus, in addition to the direct and indirect effects of socioeconomic predictors and situational action theory’s social components on the lethal violence, this study captures and examines the spatial effects concurrently.

In sum, using the spatial analysis methodology, this study initially examines the effect of socioeconomic predictors on the homicide rate, suicide rate, lethal violence rate, and suicide/homicide rate. Next, this study tests structural components of the situational action theory that mediate the variations in the homicide rate, suicide rate, lethal violence rate, and suicide/homicide rate. With above mentioned issues and previous research, this study hypothesizes for each dependent variable as follow:

1) **For the homicide rate**

\[ H_0: \] Contextual socioeconomic predictors are positively associated with the homicide rate in consideration of spatial autocorrelation among the predictors.

\[ H_1: \] Contextual predictors influencing the level of collective morality and constraint mediate the association between the socioeconomic predictors and the homicide rate in consideration of spatial autocorrelation.

2) **For the suicide rate**

\[ H_0: \] Contextual socioeconomic predictors are positively associated with the suicide rate in consideration of spatial autocorrelation among the predictors.
$H_1$: Contextual predictors influencing the level of collective morality and constraint mediate the association between the socioeconomic predictors and the suicide rate in consideration of spatial autocorrelation.

3) **For the lethal violence rate**

$H_0$: Contextual socioeconomic predictors are positively associated with the suicide rate in consideration of spatial autocorrelation among the predictors.

$H_1$: Contextual predictors influencing the level of collective morality and constraint mediate the association between the socioeconomic predictors and the suicide rate in consideration of spatial autocorrelation.

4) **For the suicide/homicide rate**

$H_0$: Contextual socioeconomic predictors are positively associated with the suicide rate in consideration of spatial autocorrelation among the predictors.

$H_1$: Contextual predictors influencing the level of collective morality and constraint mediate the association between the socioeconomic predictors and the suicide rate in consideration of spatial autocorrelation.

Additionally, as the stream analogy and the frustration-aggression approach have pointed out the different contextual effects on the different types of lethal violence, this study eventually assumes that the contextual predictors would impact the homicide rate, suicide rate, lethal violence rate, and suicide/homicide rate differently.

5) **Comparisons of contextual effects on the four types of lethal violence**

$H_0$: Contextual socioeconomic predictors affect the homicide rate, suicide rate, lethal violence rate, and suicide/homicide rate differently, in consideration of spatial autocorrelation among the predictors.

$H_1$: Contextual predictors influencing the level of collective morality and constraint mediate the association between the socioeconomic predictors and the homicide rate,
suicide rate, lethal violence rate, and suicide/homicide rate differently, in consideration of spatial autocorrelation among the predictors.
CHAPTER 5: DATA AND METHODOLOGY

5.1. Units of Analysis

Several scholars have emphasized the importance of units of analysis in spatial analyses (Rengert & Lockwood, 2009; Weisburd et al., 2009). For instance, Rengert and Lockwood (2009) noted that the interpretation of the nature of spatial associations between social phenomena is “impacted by the manner that data are aggregated into spatial units” (p.121). Thus, “the selection of units of analysis should be guided ideally by knowledge of the phenomenon under investigation” (Messner et al., 1999, p.427). However, due to the high cost of collecting their own data, it is unreasonable to expect researchers to create their own units to meet their study purposes (Tita & Radil, 2010). Tita and Radil (2010) noted that “places [ ] are never natural, preformed, or given and there is no such thing as the ‘right’ scale for any given research topic or interest” (p.474). Thus, the majority of spatial studies on lethal violence has usually utilized several sources of aggregated unit or data that is publicly available, such as U.S. census unit and adjusted census units (e.g., community units from the Project on Human Development in Chicago’s Neighborhood, which are based upon Chicago’s 865 census tracts) (Mears & Bhati, 2006).

Facing the difficulties of creating its own unit of analysis, this study chooses U.S. counties as units of analysis among many alternative geographic units from the U.S. census data, such as census blocks, census tracts, and states. The selection of the county as a unit of analysis has been supported by several social scientists (Light & Harris, 2012; Messner et al., 1999; Nielsen & Alderson, 1997). They reasoned that the county is “a common unit of measurement for data collection”; thus, several government or private institutes collect and distribute the county level data ranging from economic to political data (Messner et al., 1999). In addition, the county provides “a large enough sample size to include an adequate number of covariates” in the model.
with statistical power to detect effects (Light & Harris, 2012). The sample size represents the complete range of the U.S. social landscape and enables researchers to explore spatial patterns across areas with different structural covariates (Light & Harris, 2012; Messner et al., 1999). Moreover, there have been numerous prior research utilizing county as unit of analysis in the homicide rate (James & Cossman, 2006; James & Porter, 2012; Kposowa et al., 1995; Mencken & Barnett, 1999; Messner et al., 1999) and the suicide rate studies (Baller & Richardson, 2002; Congdon, 2009; Trgovac et al., 2015).

However, despite several desirable features of county as a unit of analysis, there are some shortcomings. As Weisburd et al. (2009) pointed out, researchers are increasingly making use of smaller spatial units of analysis, even as small as addresses or street blocks, because smaller units are more likely to have homogeneous structural features within their boundaries. In addition, the county, as a relatively large unit, might lead to a misinterpretation of geographic data by averaging the effect of lower-order unit variability (e.g., even a county with a very low crime rate might have hot spots of crime among lower-order units, such as census tracts) (Weisburd et al., 2009). Nevertheless, this study considers the county a unit of analysis due to the data availability because most structural predictors from different data sources available are aggregated at the county level.

5.2. Data Source

There are five major sources of datasets for this study.

First, for the dependent variables, the suicide rate, homicide rate, lethal violence rate and suicide/homicide rate, this study obtains the homicide rate and the suicide rate data from the National Vital Statistics System (NVSS) at the Centers for Disease and Control and Prevention (CDC). Based on the nationally standardized death certificates, the NVSS provides the cause of
death under the International Classification of Diseases, Tenth Revision (ICD-10). In nationwide studies of suicide, the NVSS has been a main source due to the lack of other alternative data collections (e.g., Moore et al., 2014; Trgovac et al., 2015; Wadsworth & Kubrin, 2007). At the same time, researchers have obtained the nationwide homicide data beyond the NVSS, such as the Supplementary Homicide Report under the Uniform Crime Reporting (UCR) program (U.S. Department of Justice, 2014). Even though there is an alternative source for homicide data, this study obtains both the homicide rate and the suicide rate data from the NVSS.

Several researchers have examined homicide data from the NVSS rather than the UCR data for the following reasons. On the one hand, the NVSS dataset “produce[s] more accurate homicide trends at national level” than the UCR because it “includes deaths that occur in federal jurisdictions and more complete state and local jurisdiction reporting” (U.S. Department of Justice, 2014, p. 4; see also Lanier, 2010). In addition, the NVSS data is simpler and more valid than its counterpart because the NVSS requires the death certificate only for its data input, and its data collection is mandatory for tracking all the deaths in the U.S. 

On the other hand, UCR data is “designed to capture homicides known to law enforcement by jurisdiction” in an attempt to voluntarily track crime statistics (U.S. Department of Justice, 2014, p. 4); thus, the UCR data shows fewer homicides than the NVSS (see also Lanier, 2010; Wiersema, Loftin, & McDowall, 2000). Even though the UCR data are appropriate for understanding detailed circumstances surrounding homicide incidents because they are based on the complex police report, this study needs only the accurate numbers of homicide and suicide, not the details of each incident. Thus, for the purpose of this study, the NVSS is the appropriate source for the homicide rate and the suicide rate. In particular, the datasets are based on the 5-year averaged rates between 2012 and 2016, which are latest and matched with the
majority of socioeconomic predictors from the U.S. Census Bureau.

The second major data source that includes several sets of structural covariates is the U.S. Census Bureau online database, American Fact Finder. By conducting a nationwide survey, the Bureau collects basic demographic or SES information at the different geographic level. This study examines the 5-year estimates between 2012 and 2016 for several demographic or SES datasets at the county level to match the dependent variables in time and geography. Using 5-year estimate dataset provides comparably consistent socioeconomic data in a wider geographic and topical scope (Donnelly, 2013).

The third data source is the U.S. Religion Census collected by the Association of Statisticians of American Religious Bodies (ASARB) in 2010. The 2010 data is used because it is the ASARB’s most recent dataset. The ASARB compiled data on the number of congregations and adherents for 236 religious groups at the county level. In 2010, 236 groups reported 344,894 congregations with 150,686,156 adherents. This study examines the effects of religiosity based on four religious denominations, Evangelical Protestants, Black Protestants, Mainline Protestants, Catholic, in addition to “others” (Steensland et al., 2000).

The fourth data source is the amount of alcohol consumption within each county. Due to the lack of county-level data, this study uses rate of alcohol-induced mortality from the NVSS at the CDC. Even though the alcohol-induced mortality rate is not a direct indicator of per capita alcohol consumption, Rehm et al. (2017) noted that the more alcohol consumed, the higher the risk of death from alcohol-related diseases, such as liver cancer. Thus, this study uses alcohol-induced death as a proxy for per capita alcohol consumption. The alcohol-induced death code under ICD-10 includes many alcohol-induced causes of death such as mental and behavioral disorders and liver disease.
The fifth data source is the Census of State and Local Law Enforcement Agencies (CSLLEA) compiled by the Bureau of Justice Statistics. The CSLLEA is conducted every four years to explore the functions and types of law enforcement agencies across the U.S. The CSLLEA provides the total number of law enforcement employees. This data is used to indicate the number of law enforcement officers per 100,000 population at the county level. Unlike other datasets compiled between 2012 and 2016, this study uses the 2008 CSLLEA datasets because they are the most recent.

5.3. Dependent Variables

The dependent variables in this study are the county homicide rate, suicide rate, lethal violence rate, and suicide/homicide rate. The homicide and suicide rates are per 100,000 population computed as the 5-year averaged rate from 2012 to 2016. This study uses these rates because as Lee and Bartkowski (2004b) have noted, homicide is a rare occurrence that might be “unduly influenced by random fluctuations” (p. 20). With a similar reason and assumption that contextual predictors persist over time and space, several researchers have used the averaged rates for homicide (e.g., Krivo & Peterson, 2000; Lee, 2006; McCall et al., 2008; Parker, 2004) and suicide (e.g., Moore et al., 2014; Recker & Moor, 2016; Wadsworth et al., 2014). However, among 3,142 counties across the U.S., this study excludes 2,144 with no suicides or homicides during the 5-year period (Trgovac et al., 2015). Thus, this study is limited to 998 counties that record both homicides and suicides. The 998 counties had a population of 270,352,276 in 2016, accounting for 84.86% of the entire U.S. population (318,558,162 people). Map 1 shows the 998 counties and the 2,144 excluded counties.

To capture the possible relationship between suicide and homicide, Gold (1958) suggested the rates of lethal violence and suicide/homicide. The former is the sum of the
homicide rate and the suicide rate; the latter is measured by dividing the suicide rate by the sum of the homicide rate and the suicide rate. A higher suicide/homicide rate indicates that the lethal violence is more likely manifested by suicide than by homicide (Gold, 1958; Wu, 2003). Based on the homicide rate and the suicide rate of 998 counties, this study computes the lethal violence rate and suicide/homicide rate, as Gold (1958) suggested. Table 1 shows the descriptive statistics on the four dependent variables in this study.

Table 1. Descriptive statistics on the dependent variables.

<table>
<thead>
<tr>
<th>Dependent Variables</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Homicide Rate</td>
<td>0.60</td>
<td>39.46</td>
<td>6.39</td>
<td>4.75</td>
</tr>
<tr>
<td>Suicide Rate</td>
<td>5.06</td>
<td>39.36</td>
<td>15.50</td>
<td>4.92</td>
</tr>
<tr>
<td>Lethal Violence rate</td>
<td>7.99</td>
<td>58.03</td>
<td>21.89</td>
<td>6.77</td>
</tr>
<tr>
<td>Suicide/Homicide Rate</td>
<td>0.18</td>
<td>0.95</td>
<td>0.72</td>
<td>0.14</td>
</tr>
</tbody>
</table>

5.4. Explanatory Variables

Even though this study examines the effects of the structural components of situational action theory on lethal violence, it also accepts the assumptions and findings of previous studies on the relationship between socioeconomic predictors and lethal violence. Thus, this study initially tests the direct effects of these predictors on lethal violence as the main pathway. Thereafter, this study identifies structural components of situational action theory that mediate the variations in the dependent variables. For the direct effects, this study examines the effects of absolute- and relative-deprivation indicators and divorce rates within counties.

5.4.1. Combined Absolute Deprivation

Relying on previous findings on the association between the absolute deprivation indices
and the lethal violence, this study tests several variables indicating such deprivation. To avoid multicollinearity, previous researchers have combined several economic indicators into a single disadvantage index (e.g., DeFronzo & Hannon, 1998; Kubrin, 2003; MacDonald & Gover, 2005; McCall et al., 2010). Relying on these studies, this study integrates four economic predictors into one variable by conducting the principal components factor analysis as shown in table 2. The four variables are unemployment rate, percentage of food stamp recipients, percentage of population living below the poverty line, and percentage of bachelor’s degree holders. This indicator is the combined-absolute deprivation.

**Table 2. Principal components factor analysis on absolute deprivation.**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Factor 1 Combined Absolute Deprivation</th>
<th>Uniqueness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment Rate</td>
<td>0.83</td>
<td>0.30</td>
</tr>
<tr>
<td>Food Stamp</td>
<td>0.93</td>
<td>0.13</td>
</tr>
<tr>
<td>Below Poverty Line</td>
<td>0.90</td>
<td>0.19</td>
</tr>
<tr>
<td>Bachelor’s Degree</td>
<td>-0.82</td>
<td>0.33</td>
</tr>
</tbody>
</table>

5.4.2. Relative Deprivation

Relative deprivation is conceptualized by disparities in the distribution of wealth (Pratt & Cullen, 2005; see also Harer & Steffensmeier, 1992). To capture the unequal distribution of wealth, this study uses the Gini coefficient at the county level. In addition to the Gini indices, this study considers racial disparities in the unemployment rate (e.g., Harer & Steffensmeier, 1992; Wadsworth & Kubrin, 2007). This study examines two ratios of unemployment rate: one between Blacks and Whites and the other between Hispanics and Whites. These variables are computed by dividing the unemployment rate of two non-White groups by that of White. The descriptive statistics are presented in table 3.
5.4.3. Divorce Rate

Several researchers have tested the effects of divorce on lethal violence as proxies for social integration and cohesion (e.g., Moore et al., 2014; Stack & Wasserman, 1995). Previous studies have found that the divorce rate has a strong and stable effect on the homicide rate (e.g., Pratt & Cullen, 2005) and the suicide rate (e.g., Cutright & Fernquist, 2005; Recker & Moore, 2016). Thus, this study includes the percentage of divorced population in each county as an explanatory variable (table 3).

Table 3. Descriptive statistics on explanatory variables.

<table>
<thead>
<tr>
<th>Control Variables</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absolute Deprivation</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Combined Absolute Deprivation</td>
<td>-2.56</td>
<td>3.39</td>
<td>0.07</td>
<td>0.94</td>
</tr>
<tr>
<td>Relative Deprivation</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gini Coefficients</td>
<td>0.35</td>
<td>0.60</td>
<td>2.09</td>
<td>1.00</td>
</tr>
<tr>
<td>Black/White Unemployment Ratio</td>
<td>0</td>
<td>8.38</td>
<td>2.09</td>
<td>1.00</td>
</tr>
<tr>
<td>Hispanic/White Unemployment Ratio</td>
<td>0</td>
<td>10.64</td>
<td>1.37</td>
<td>0.84</td>
</tr>
<tr>
<td>Family Disruption</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Divorce Rate</td>
<td>5.80</td>
<td>18.00</td>
<td>11.78</td>
<td>1.98</td>
</tr>
</tbody>
</table>

5.5. Mediating Variables

After examining the direct effects of socioeconomic predictors on lethal violence, this study tests the mediating effects of components of situational action theory on the relationship in the initial stage. The structural components of situational action theory examined in this study are contextual predictors that presumably affect collective morality and constraints, such as religiosity, alcohol consumption, and number of police officers within counties, all of which
influenced the suicide and/or homicide rate in previous studies.

Indirect effects are calculated by the difference of coefficient approach in the mediation model (Judd & Kenny, 1981). This study computes the indirect effects as the difference between two regression coefficients: one in the full model and the other without mediating variables. Although there are several ways to calculate the indirect effects, including product of coefficients (Sobel, 1982), this study uses the difference of coefficient approach suggested by Judd and Kenny (1981). This study uses that approach because it considers several mediating variables, not just one. When several mediating variables are considered in the analysis, other methods of calculating the mediating effects might not be appropriate because other methods need a single mediating variable to calculate the indirect effects. Moreover, the proportion of meditation is calculated by dividing the indirect by the total effect, which is sum of the direct and indirect effects (Cunliffe, 2015).

5.5.1. Religious Denominations

Several researchers have identified the negative impacts of religion on homicide (e.g., Lee & Bartkowski, 2004a; Lester, 1987; Maume & Lee, 2003) and suicide rates (e.g., Lester, 1987; Stack & Wasserman, 1995). Thus, relying on several studies, this study uses a set of variables in relation to religious denominations. Based on the religion classification scheme suggested by Steensland et al. (2000) and by the ASARB, this study categorizes the religious denominations as Evangelical Protestant, Mainline Protestant, Black Protestant, Catholic, and Others (e.g., Beyerlein & Hipp, 2005). Each variable indicates the number of believers per 100,000 people for each denomination within each county in 2010.

5.5.2. Alcohol Consumption Rate

In addition, several researchers have found that the per capita consumption of alcohol is
associated with the number of homicides (e.g., Stack, 2000; Parker et al., 2011) and suicides (e.g., Kerr et al., 2011; Landberg, 2009; Phillips, 2013). Some researchers have pointed out that the level of alcohol consumption affects the level of lethal violence in interaction with drinking patterns and other contextual predictors, such as lack of social control or the divorce rate (Miles, 2012). In addition, researchers have argued that individuals are more likely to fail to exercise the active constraint that prevents violent behaviors (Parker, 1995; Ramstedt, 2001). Drawing on the previous research, this study includes the alcohol-induced mortality rate per 100,000 populations as a proxy for alcohol consumption.

5.5.3. Number of Police

Even though there have been mixed results, researchers have examined the effects of police presence on the homicide rate. The numbers of police or law enforcement officers have been used as a proxy for the level of external or social control. By the nature, suicide is not the type of violent behavior that is affected by the police presence; thus, the presence is expected to affect only the HR. This possible change in the homicide rate due to the police presence might have an indirect effect on the suicide/homicide rate. Thus, this study includes the number of police officers within each county to examine whether the presence of police significantly influences the homicide rate and the suicide/homicide rate. The descriptive statistics on the three situational action theory’s structural component indicators are summarized in table 4.

Table 4. Descriptive statistics on the situational action theory components.

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Religious Denominations</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Evangelical Protestant</td>
<td>4.92</td>
<td>669.89</td>
<td>232.19</td>
<td>148.34</td>
</tr>
<tr>
<td>Black Protestant</td>
<td>0</td>
<td>312.60</td>
<td>22.89</td>
<td>35.13</td>
</tr>
</tbody>
</table>
5.6. Control Variables

This study examines the effects of two groups of contextual variables: 1) socioeconomic variables as direct effect and 2) structural components of situational action theory as indirect effect. Thus, some variables that have been empirically found to affect the suicide and homicide rates are controlled to test the pure effects of two variable groups. The controlled variables include age structure, gender ratio, and racial group indicators.

5.6.1. Age Structure

Previous researchers have found that the age structures are strong predictors of lethal violence. Even though the results have been mixed, the level of youth population is positively associated with the high level of homicide whereas elderly populations are positively associated with the suicide rate (e.g., Bainbridge, 1989; Marvell & Moody, 1991). Thus, this study includes and controls the two age-specific groups, young and elderly population. The young population is measured by the percentage of population between 20 and 34 years of age whereas the elderly population is measured by the percentage of population of 65 years of age or older within each county.

5.6.2. Gender Ratio

Even though there have been a few studies, some researchers have examined the
contextual effects of gender ratio on the homicide rate (McCall et al., 2013) and the suicide rate (Phillips & Nugent, 2014). Similar to the age structure variables, this study includes and controls the population structure based on gender. The gender ratio is measured by dividing the proportion of male population within in each county by the proportion of female.

5.6.3. Racial Groups

Previous research has measured ethnic heterogeneity by focusing on either specific racial groups (e.g., Krivo & Peterson, 2000; Messner, 1982) or ethnic groups as a whole (e.g., Chavez & Griffiths, 2009; Wadsworth, 2010). Following the latter approach, which has produced consistent results, this study controls the two ethnic heterogeneity indicators, foreign born and new immigrants (Chavez & Griffiths, 2009). The foreign-born variable is measured by the proportion of populations within each county who were born outside of U.S.; the new immigrant variable is measured by the proportion of the population that moved into each county one year before the Census Bureau collected the data in each year. Three control variables are summarized in table 5.

**Table 5.** Descriptive statistics on the three types of control variables.

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age Structure</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Young Population</td>
<td>8.10</td>
<td>39.30</td>
<td>19.94</td>
<td>3.71</td>
</tr>
<tr>
<td>Elderly Population</td>
<td>7.10</td>
<td>53.10</td>
<td>15.42</td>
<td>3.95</td>
</tr>
<tr>
<td><strong>Gender Ratio</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male/Female Ratio</td>
<td>0.84</td>
<td>1.97</td>
<td>0.97</td>
<td>0.07</td>
</tr>
<tr>
<td><strong>Immigration</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Foreign Born</td>
<td>0</td>
<td>18.54</td>
<td>1.13</td>
<td>1.10</td>
</tr>
<tr>
<td>New Immigrants</td>
<td>0</td>
<td>30.30</td>
<td>7.90</td>
<td>3.87</td>
</tr>
</tbody>
</table>
5.7. **Missing Data**

Missing data in a systemic fashion can result in potentially biased findings and problems with generalizability (Schwartz & Beaver, 2014). In particular, missing data in spatial analysis might be more problematic because the one observation is spatially interrelated with other observations (e.g., Arbia, Espa, & Giuliani, 2016; Boehmke, Schilling, & Hays, 2015; Kelejian & Prucha, 2010). Several previous studies have taken different approaches to compensate for missing data. Based on the assumption that contextual predictors cluster together within a certain area and persist despite social or ecological changes (Sampson, 2011, 2013), mean replacement and multiyear average techniques have been commonly employed (Andersson, 2015; Chon, 2013). This study uses the multiyear average because homicide is relatively rare; some counties reported no homicides in some years over the five-year period. Use of multiyear average is supported by the notion that contextual predictors persist over time and space (e.g., Krivo & Peterson, 2000; Lee, 2006; McCall et al., 2008; Parker, 2004).

5.8. **Analytical Strategy**

This study examines the effects of social contexts on the homicide rate, suicide rate, lethal violence rate, and suicide/homicide rate independently using the techniques of spatial analysis. This study uses the GeoDa statistical package. The GeoDa provides researchers with different spatial analysis tools “starting with simple mapping and geovisualization, moving on to exploration, spatial autocorrelation analysis, and ending up with spatial regression” (Anselin, Syabri, & Kyo, 2006, p. 6). Due to the spatial nature of the datasets, the units of analysis in this study, counties, which are in close geographical proximity, are more likely to have similar social contexts (Messner et al., 1999; Sampson, 2013). This spatial dependence or autocorrelation is a violation of the OLS regression assumptions on the independence of observations; thus,
overlooking the spatial dependence leads to the unstable parameter estimates and unreliable significant tests (Chon, 2013; Messner & Anselin, 2004; Cossman, Cossman, James, Campbell, Blanchard, & Cosby, 2007). The spatial regressions under the GeoDa calculate the spatial interdependence in the units of analysis and eliminate spatial dependence issues in the spatial dataset. This spatial dependence issue is a compelling reason for using the GeoDa statistical package in this study. To examine the effects of social contexts with the spatial analysis technique, this study utilizes two-phase analysis (Porter & Purser, 2010). This study presents a descriptive and exploratory examination of each variable to show spatial autocorrelation or spatial dependence. Then, based on spatial dependence identified in the first phase, this study implements a spatial regression model to examine the effects of social contexts on lethal violence.

5.8.1. Exploratory Spatial Data Analysis

In the first phase, this study identifies the simple distribution of data and possible clustering in the dataset using Exploratory Spatial Data Analysis (ESDA). The ESDA reveals spatial patterns in data, describes and visualizes the spatial distribution, and then identifies typical and outlying locations (Messner et al., 1999). The ESDA is especially useful to identify spatial dependence. The ESDA techniques used in this study are Moran’s I and Anselin’s local indictor of spatial association (LISA).

Ranging from -1 to 1, the Moran’s I shows statistical similarities in places that are close together. Similar to the zero-order correlation, the positive values for Moran’s I indicate “places close together are statistically more alike and a negative coefficient indicates that place close together tend to be dissimilar to one another” (Porter & Purser, 2010, p. 945). The Moran’s I can be presented as
\[ I = \frac{1}{s^2} \sum_{i=1}^{N} \sum_{j=1}^{N} \omega_{ij} (Y_i - \bar{Y}) (Y_j - \bar{Y}) \], \quad s^2 = \frac{1}{N} \sum_{i=1}^{N} (Y_i - \bar{Y})^2

where the product of each unit \((i)\) minus overall mean \((\bar{Y})\) and each neighborhood \((j)\) minus the overall mean is divided by the weight indicator \((\omega_{ij})\) that is summed across all units and neighborhoods (Porter & Purser, 2010). Thus, the Moran’s I indicates that areas in closer proximity are more likely to be similar or dissimilar than those that are far apart (Porter & Purser, 2010).

Next, after checking global spatial dependence in the dataset with Moran’s I, this study examines potential clustering at the local level by using LISA. LISA is “based upon Moran’s I coefficient decomposed into a ‘local’ level” (Porter & Purser, 2010, p.945; see also Anselin, 1995). LISA produces categorical outcome that are indicative of positive or negative spatial clustering or random spatial distribution. LISA can therefore be presented as

\[ I_i = \sum_{j=1}^{N} \omega_{ij} (Y_i - \bar{Y}) (Y_j - \bar{Y}) \]

where the weight indicator \((\omega_{ij})\) is multiplied by the product of each unit \((i)\) minus overall mean \((\bar{Y})\) and each neighborhood \((j)\) minus the overall mean (Porter & Purser, 2010). Thus, the LISA indicates the relationship of one unit to the remaining units within the \(j^{th}\) neighborhood.

Moreover, the spatial weights matrix is a prerequisite component to calculate the Moran’s I and the LISA. The spatial weight identifies “who is a neighbor and who is not, or with whom an actor interacts” (Tita & Radil, 2010, p.111). The spatial weight is essential to define the form and limits of the spatial dependence and to formalize the interactions between the locations; thus, the misspecification of the spatial weights has a profound effect on the estimation of spatial dependence (Bhattacharjee & Jensen-Butler, 2013; Tita & Radil, 2010). There are several types of spatial weights matrix, but they are “based either on simple contiguity, \(k\)-nearest neighbors, or
the use of distance decay metrics (Tita & Radil, 2010, p. 112). In preliminary analyses, this study tests each spatial weight matrix by running GeoDa package tool and finds that the first order queen continuity has the most significant coefficient values in the spatial dependence. Thus, this study uses the first order of queen as spatial weights matrix not only for the ESDA, but also for the multivariable spatial regression analysis.

### 5.8.2. Multivariable Spatial Regression Analysis

In the second phase, this study identifies “the appropriate technique to control for the existence or absence of spatial autocorrelation” before conducting spatial regression analysis (Porter & Purser, 2010, p. 945). To select a proper spatially weighted model between spatial lag and error model, this study runs spatial dependency diagnostics in GeoDa. In reference to the Lagrange Multiplier (LM) and Robust LM statistics, this study identifies whether the spatial dependence is caused by either error or lag.

When the dependence is proven to have been caused by error, the spatial weight is applied to error term in regression equation (spatial error model). The error model can be presented as

\[ Y = X\beta + \varepsilon, \quad \varepsilon = \lambda W\varepsilon + \mu \]

where \( Y \) is the dependent variable; \( X \) is the independent variable; \( \varepsilon \) is the vector of error terms; \( W \) is the spatial weight; \( \lambda \) is the autoregression parameter; and \( \mu \) is the vector of uncorrelated, homoscedastic errors (Baller et al., 2001; Tita & Radil, 2010). On the one hand, “the essence of this expression is that the value of the dependent variable for each location is affected by the stochastic errors at all locations through the spatial multiplier” (\( \lambda W \)) (Baller et al., 2001, p. 571). On the other hand, when spatial dependence is proven to be associated with substance (lag), the
spatial weight is applied to the dependent variable (spatial lag model). The spatial lag model can be presented as

\[ Y = \rho Wy + X\beta + \epsilon \]

where \( \rho \) is the autoregression parameter; \( W \) is the spatial weight; and \( \epsilon \) is the error term (Baller et al., 2001; Tita & Radil, 2010). The spatial lag model indicates that the outcome variable depends not only on the independent variable within a location, but also on that of other neighboring locations. (Baller et al., 2001). Thus, depending on the result of the spatial dependency diagnostics, this study chooses one of these two models and performs the corresponding spatial regression analysis.

In conclusion, applying this two-pronged test, this study presents spatial distribution and possible spatial clustering of the homicide rate, suicide rate, lethal violence rate, and suicide/homicide rate at the first stage of analysis. Next, based on the spatial dependence, this study runs OLS diagnostics to determine the appropriate type of spatial model (error or lag) for model specification. Finally, based on this decision, a series of additive models is examined, focusing on the socioeconomic predictors and the social components of social action theory, while controlling other social contextual features.
CHAPTER 6: RESULTS

This study conducts a series of spatial analysis with the collected datasets. This study explores the possible spatial autocorrelation within each dependent variable, and autocorrelation is a prerequisite for further analysis. Applying the ESDA technique, this study finds that spatial autocorrelation for all dependent variables, but with different strengths (figures 2 through 5). The suicide rate shows a particularly strong spatial autocorrelation indicated by the high Moran’s I value (0.51). This indicates that the suicide rate within a county is strongly influenced by the adjacent counties. The other three dependent variables—lethal violence rate (0.41), suicide/homicide rate (0.34), and homicide rate (0.29)—also show a strong spatial autocorrelation. These results demonstrate that lethal violence in the U.S. counties is not randomly distributed and is not in isolation. They are contagious between counties. Consistent with previous studies, such interaction is affected by propinquity, and features of a county spill over into the adjacent counties (Messner et al., 199; Tobler, 1970).

Although it is not shown in this study, when examining the spatial dependence with different orders of queen continuity, the first order of queen has the highest Moran’s I coefficient for each dependent variable. Thus, this study uses the first order as the spatial weight across all models in further analyses. Based on the spatial autocorrelation, this study examines each dependent variable with a series of different spatial statistical techniques, including LISA and multivariable spatial regression.

6.1 Association between the Homicide Rate and the Structural Covariates

Based on the spatial autocorrelation in the homicide rate, this study tests the effects of structural covariates on the homicide rate. In this section, this study first examines descriptive statistics on the homicide rate by using bivariate correlation and LISA indicator. Then, this study explores the relationships between the homicide rate and structural covariates with three different
multivariable spatial regression models. The controlled, direct, and mediating models are shown in table 7. Replications of these three models are carried out for other three dependent variables in the later sections.

### 6.1.1. Descriptive Statistics on the Homicide Rate and the Structural Covariates

Table 6 presents bivariate correlations between the homicide rate and other variables. The homicide rate is positively and significantly correlated with a population aged between 20 and 34 ($r=0.08$, $p<0.05$), divorce rate ($r=0.15$, $p<0.001$), combined absolute deprivation ($r=0.60$, $p<0.001$), Gini coefficient ($r=0.42$, $p<0.001$), Black/White unemployment ratio ($r=0.15$, $p<0.001$), Evangelical Protestant ($r=0.25$, $p<0.001$), Black Protestant ($r=0.58$, $p<0.001$), alcohol mortality rate ($r=0.11$, $p<0.001$), and number of police ($r=0.16$, $p<0.001$).

The homicide rate is also negatively and significantly associated with gender ratio ($r=-0.10$, $p<0.01$), foreign born ($r=-0.15$, $p<0.001$), immigrants ($r=-0.14$, $p<0.001$), Catholic ($r=-0.17$, $p<0.001$), and other religion ($r=-0.09$, $p<0.01$). These associations between the homicide rate and structural predictors are consistent with those found in previous studies. In particular, several studies under different criminological theories have found that disadvantaged social and economic conditions negatively impact the homicide rate (Pridemore, 2002).

Map 2-1 presents the geographic distribution of the homicide rate across the U.S. at the county level. According to the map, the homicide rate is not evenly distributed. For instance, the southern U.S. has a higher homicide rate than the northern. Counties with the homicide rate between 8.1 and 39.5 are clustered in the southeastern areas, including Louisiana, Florida, Georgia, and South Carolina whereas counties with lower homicide rate are concentrated in the Midwest and northern areas. This visual geographic concentration of the high homicide rate indirectly supports the spatial autocorrelation indicated by Moran’s I.
In addition to Moran’s I, this study examines the homicide rate with LISA. LISA produces categorical outcome indicating positive or negative spatial clustering at the more localized level. As seen in map 2-2, high homicide rates are found in the southeastern areas.
(High-High) but low homicide rates are found along the New England coastline (Low-Low). In addition, some small clusters of low homicide rates (Low-Low) are scattered across the U.S., including Colorado and Washington state. These results indicate when the homicide rate increases in the High-High counties, so does the homicide rate in surrounding counties; however, in the Low-Low counties, the low homicide rate is positively related to the low homicide rates in surrounding counties. These results demonstrate that lethal violence in the U.S. is not randomly distributed at the county level. These spatial dependencies and clusters are accurate indicators not only for descriptive purposes, but also for multivariable spatial regression analysis (Porter & Purser, 2010).

6.1.2. Multivariable Spatial Regression Model for the Homicide Rate

Table 7 presents the findings from the multivariable spatial regression models for the homicide rate. To select a proper spatially weighted model between spatial lag and spatial error, this study conducts spatial dependency diagnostics with the GeoDa package. In reference to the Lagrange Multiplier (LM) and the robust LM statistics, this study uses the spatial error model over spatial lag. For instance, both LMs for the spatial lag and error models are statistically significant; however, the robust LM is statistically significant only for the spatial error. Thus, this study identifies that the suitable models for the homicide rate analysis are spatial error models as presented in table 7.

Model 1 in table 7 includes control variables, indicators of demographic features, and illustrates that these variables explain little variation in the homicide rate \( R^2 = 0.172 \), as compared to the following models, Model 2 \( R^2 = 0.483 \) and Model 3 \( R^2 = 0.568 \). Model 1 indicates that population age between 20 and 34 \( b = 0.236, p < 0.001 \) is positively associated with the homicide rate but gender ratio \( b = -8.677, p < 0.001 \), foreign born \( b = -0.343, p < 0.05 \), and
immigrants ($b=-0.175, p<0.001$) are negatively associated with the homicide rate. Population age over 65 is not statistically significant.

In model 2, several socioeconomic predictors are added as direct effects on the HR. The table shows that the absolute deprivation indicator ($b=2.658, p<0.001$) and the Gini coefficient ($b=34.712, p<0.001$) are positively associated with the homicide rate. These significant effects on the homicide rate remain consistent in model 3. At the same time, three other predictors, the Hispanic/White unemployment ratio, the Black/White unemployment ratio, and the divorce rate, are found not significant. Their non-significant effects remain consistent in model 3. Among these three variables, the finding for the divorce rate is not consistent with the majority of previous studies, which found stable and positive effects of divorce rate on lethal violence (Pridemore, 2002). Non-significant effects of divorce rate might be explained by the strong effects of other two economic predictors, the combined absolute deprivation and the Gini coefficient. As Messner and Tardiff (1986) noted, effects of divorce rate on the homicide rate originate from the reciprocal causal relations with other socioeconomic predictors, the effects of divorce rate might have been offset by those of other two predictors in this study. The inclusion of socioeconomic variables generates some changes in the demographic feature indicators. Population age between 20 and 34, foreign born, and immigrants cease to be significant and population age over 65 does become significant ($b=-0.196, p<0.001$).

Lastly, model 3 presents the full model incorporating all variables including mediating variables, the situational action theory component indicators. This study finds that alcohol consumption indicator ($b=0.061, p<0.01$), Black Protestant ($b=0.053, p<0.001$), and the number of police officers ($b=0.001, p<0.05$) have statistically significant and positive effects on the homicide rate. Among these three significant predictors, results for the alcohol consumption are
consistent with those of previous studies that found a positive relationship between drinking patterns and the homicide rate (Miles, 2012; Norström, 2011). In addition, not many studies have examined the effects of Black Protestant on the homicide rate, but this study finds a strong effect on the homicide rate. This finding might be indirectly supported by the state study that found the percentage of Black Baptists in some southern states were positively correlated with the homicide rate whereas White Protestants were negatively associated with the homicide rate in some other southern states (Wasserman, 1978). The results for the police indicator contradicts some previous studies that found the negative effects of police presence on the homicide rate (Parker, 2004). It is possible that overreliance on public controls, such as police presence, may diminish the capacity of informal controls, eventually resulting in more crime (Rose & Clear, 1998). Alternatively, the criminal justice system in counties with many homicides tend to deploy more law enforcement officers and spend more to fight crimes (e.g., Jackson & Carroll, 1981).

Some changes occur after adding situational action theory component indicators in model 3. The table shows that the only significant predictors among demographic feature indicators is population age over 65 ($b=-0.183$, $p<0.001$). Also, in consideration of controlled and mediating effects, the standardized coefficients for combined absolute derivation ($\Delta b=0.643$) and Gini coefficient ($\Delta b=14.211$) slightly decrease. The difference of the two coefficients before and after introduction of mediating variables presents the indirect effects of mediating variables (Judd & Kenny, 1981). The proportion of mediating effects of each variable is calculated by dividing the indirect effect by the total effect, which is sum of direct and indirect effect (Cunliffe, 2015). The proportion of mediating effect for each significant socioeconomic predictor is 19.4% for absolute deprivation and 29.0% for Gini coefficient. Thus, the results suggest the social component of the social action theory mediates the effects of socioeconomic predictors on the
homicide rate. Based on the results from the three models in table 7, the relationships among all variables are depicted in figure 6.

Table 7. Controlled, Direct, and Mediating Effects on the HR (Spatial Error Models)

<table>
<thead>
<tr>
<th>Structural Predictors</th>
<th>Model 1 (Control)</th>
<th>Model 2 (Direct)</th>
<th>Model 3 (Full Model)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Controlled Effects</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Demographic Features</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (20-34)</td>
<td>0.236***</td>
<td>-0.055</td>
<td>-0.048</td>
</tr>
<tr>
<td>Age (over 65)</td>
<td>0.068</td>
<td>-0.196***</td>
<td>-0.183***</td>
</tr>
<tr>
<td>Gender Ratio</td>
<td>-8.677***</td>
<td>-5.523**</td>
<td>-2.216</td>
</tr>
<tr>
<td>Foreign Born</td>
<td>-0.343*</td>
<td>-0.135</td>
<td>-0.037</td>
</tr>
<tr>
<td>Immigrants</td>
<td>-0.175***</td>
<td>0.016</td>
<td>0.015</td>
</tr>
<tr>
<td><strong>Direct Effects</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Socio-Economic Status</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Absolute Deprivation</td>
<td>-</td>
<td>2.658***</td>
<td>2.015***</td>
</tr>
<tr>
<td>GINI</td>
<td>-</td>
<td>34.712***</td>
<td>20.501***</td>
</tr>
<tr>
<td>Hispanic/White Unemployment</td>
<td>-</td>
<td>0.193</td>
<td>0.172</td>
</tr>
<tr>
<td>Black/White Unemployment</td>
<td>-</td>
<td>0.158</td>
<td>0.022</td>
</tr>
<tr>
<td>Divorce Rate</td>
<td>-</td>
<td>0.130</td>
<td>0.129</td>
</tr>
<tr>
<td><strong>Mediating Effects</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Situational Action Theory Components</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Evangelical Protestant</td>
<td>-</td>
<td>-</td>
<td>-0.001</td>
</tr>
<tr>
<td>Black Protestant</td>
<td>-</td>
<td>-</td>
<td>0.053***</td>
</tr>
<tr>
<td>Mainline Protestant</td>
<td>-</td>
<td>-</td>
<td>0.000</td>
</tr>
<tr>
<td>Catholic</td>
<td>-</td>
<td>-</td>
<td>0.000</td>
</tr>
<tr>
<td>Other</td>
<td>-</td>
<td>-</td>
<td>0.000</td>
</tr>
<tr>
<td>Alcohol-Induced Mortality Rate</td>
<td>-</td>
<td>-</td>
<td>0.061**</td>
</tr>
<tr>
<td>Police</td>
<td>-</td>
<td>-</td>
<td>0.001*</td>
</tr>
<tr>
<td><strong>Spatial Parameter (Lambda)</strong></td>
<td>0.320***</td>
<td>0.315***</td>
<td>0.291***</td>
</tr>
<tr>
<td>Constant</td>
<td>10.459***</td>
<td>-2.378</td>
<td>-1.151</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.172</td>
<td>0.483</td>
<td>0.568</td>
</tr>
<tr>
<td>AIC</td>
<td>5371.600</td>
<td>4939.580</td>
<td>4781.530</td>
</tr>
</tbody>
</table>

*: p < .05; **: p < .01; ***: p < .001
6.2. Association between the Suicide Rate and the Structural Covariates

Similar to the homicide rate analysis in the previous section, this study examines the descriptive statistics on the suicide rate and then tests the effects of structural covariates on the suicide rate with the three additive multivariable spatial regression models.

6.2.1. Descriptive Statistics on the Suicide Rate and the Structural Covariates

Table 8 presents bivariate correlations between the suicide rate and the contextual variables. The suicide rate is positively and significantly correlated with population age over 65 ($r=0.443, p<0.001$), gender ratio ($r=0.19, p<0.001$), divorce rate ($r=0.58, p<0.001$), combined absolute derivation indicator ($r=0.14, p<0.001$), Evangelical Protestant ($r=0.13, p<0.001$), other religion ($r=0.07, p<0.05$), and alcohol mortality rate ($r=0.56, p<0.001$). The suicide rate is also negatively and significantly associated with population age between 20 and 34 ($r=-0.30, p<0.001$), foreign born ($r=-0.19, p<0.001$), Gini coefficient ($r=-0.13, p<0.001$), Black/White unemployment ratio ($r=-0.19, p<0.001$), Black/White unemployment ratio ($r=-0.10, p<0.01$), Black Protestant ($r=-0.19, p<0.001$), Mainline Protestant ($r=-0.12, p<0.01$), Catholic ($r=-0.20, p<0.001$), and police ($r=-0.19, p<0.001$).

Map 3-1 depicts the geographic distribution of the suicide rate at the county level. The distribution is far from random, evidenced by the several clusters of the suicide rate across the U.S. In particular, counties with the suicide rate between 18.1 and 39.4 are concentrated in certain areas, including Washington state, Oregon, California, Arizona, New Mexico, and Florida. This visual geographic concentration of the suicide rate corroborates the existence of spatial autocorrelation indicated by Moran’s I (0.51) in the previous section. Moreover, as seen in map 3-2, the high levels of suicide rate (High-High) are found in the mid-West Coast areas, including northern California, Arizona, and New Mexico. Low suicide rates (Low-Low) are found in southern California and along the coastline in New England. These results mean when
the suicide rate increases in High-High counties, those of surrounding counties also increase; however, in the Low-Low counties, the low homicide rate is positively related to the low suicide rate in neighboring counties. These findings prove the existence of spatial autocorrelation in the suicide rate at the local level.

**Map 3-1. Geographic Distribution of the SR across the U.S. Counties**

![Map 3-1](image1)

**Map 3-2. Scatter Plot Map of the SR Based on LISA**

![Map 3-2](image2)
6.2.2. **Multivariable Spatial Regression Model for the Suicide Rate**

Table 9 shows the findings from the multivariable spatial regression models for the suicide rate. Similar to the models in the homicide rate analysis, this study uses the spatial error model over spatial lag in reference to the LM and the robust LM statistics.

Model 1 includes control variables and illustrates that demographic indicators explain variations in the suicide rate ($R^2=0.539$) more than those in the homicide rate ($R^2=0.172$). Also, within three suicide rate models, the model of best fit occurs when all variables are incorporated in model 3 ($R^2=0.697$). The table shows that the population age over 65 ($b=0.468$, $p<0.001$) and gender ratio ($b=12.160$, $p<0.001$) are positively associated with the suicide rate whereas the population age between 20 and 34 ($b=-0.089$, $p<0.05$) is negatively associated. The positive effects of population age over 65 and gender ratio remain consistent in model 2 and model 3. The effects of elderly population group on the suicide rate confirm the results of previous study finding a positive relationship between median age and the suicide rate (Gove & Hughes, 1980; Moore et al., 2014; Recker & Moore, 2016). Neither foreign born nor immigrant is statistically significant as a predictor of the suicide rate.

In model 2, this study incorporates several socioeconomic predictors as direct effects on the suicide rate. The table shows that the divorce rate ($b=0.890$, $p<0.001$) is significantly and positively associated with the suicide rate; the Gini coefficient ($b=-13.348$, $p<0.001$) and Black/White unemployment ratio ($b=-0.349$, $p<0.01$) are negatively associated. The combined absolute deprivation indicator and Hispanic/White unemployment ratio are not found to be significant. These significant or non-significant effects on the suicide rate remain consistent in model 3. An intriguing finding is that the effects of socioeconomic predictors on the suicide rate are different from the homicide rate. In particular, the Gini coefficient does affect the suicide rate
\((b=-13.348)\) and the homicide rate \((b=34.712)\) in opposite directions in model 2. These findings may be explained by previous findings that relative deprivation results in feelings of resentment and hostility to society and others; thus, people who experience deprivation might vent their resentment against others rather than against themselves (Messner, 1989; Messner & Tardiff, 1986).

This explanation for the effect of relative deprivation is supported by the reasoning of stream analogy noting that when frustration is global, individuals tend to perceive themselves as helpless to control their frustration and to blame themselves (Whitt, 1994). Thus, counties with a high Gini coefficient tend to have more people turning their anger against others, leading to the high homicide rate. Inclusion of such predictors make some changes in the demographic feature indicators. Population age between 20 and 34 is not significant but being foreign born is \((b=-0.274, p<0.001)\). The negative effects of foreign born remain consistent in model 3.

Finally, model 3 presents the full model containing all variables. As seen in the model, Evangelical Protestant \((b=0.003, p<0.01)\), other religion \((b=0.007, p<0.001)\), and alcohol consumption \((b=0.268, p<0.01)\) are positively associated with the suicide rate whereas the Black Protestant \((b=-0.014, p<0.001)\) is negatively associated. Number of police officers and the two other religious denominations are not found to be significant. This study finds that in consideration of controlled and mediating effects, the standardized coefficients for Gini coefficient \((\Delta b=0.444)\), Black/White unemployment ratio \((\Delta b=0.130)\), and divorce rate \((\Delta b=0.139)\) slightly decrease. The difference of the two coefficients presents the indirect effects of mediating variables (Judd & Kenny, 1981). The proportion of mediating effect for each significant socioeconomic predictor is 3.2% for Gini coefficient, 27.1% for Black/White unemployment ratio, and 13.5% for divorce rate.

Similar to those of homicide rate, results suggest the social action theory’s social component
mediates the effects of socioeconomic predictors on the suicide rate. Based on the results from the three models in table 9, the relationships among all variables are depicted in figure 7.

Table 9. Controlled, Direct, and Mediating Effects on the SR (Spatial Error Models)

<table>
<thead>
<tr>
<th>Controlled Effects</th>
<th>Demographic Features</th>
<th>Structural Predictors</th>
<th>Model 1 (Control)</th>
<th>Model 2 (Direct)</th>
<th>Model 3 (Full Model)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Age (20-34)</td>
<td></td>
<td>-0.089*</td>
<td>0.045</td>
<td>0.019</td>
</tr>
<tr>
<td></td>
<td>Age (over 65)</td>
<td></td>
<td>0.468***</td>
<td>0.392***</td>
<td>0.290***</td>
</tr>
<tr>
<td></td>
<td>Gender Ratio</td>
<td></td>
<td>12.160***</td>
<td>8.389***</td>
<td>7.681***</td>
</tr>
<tr>
<td></td>
<td>Foreign Born</td>
<td></td>
<td>-0.175</td>
<td>-0.274*</td>
<td>-0.247*</td>
</tr>
<tr>
<td></td>
<td>Immigrants</td>
<td></td>
<td>0.037</td>
<td>0.016</td>
<td>0.020</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Direct Effects</th>
<th>Socio-Economic Status</th>
<th>Structural Predictors</th>
<th>Model 1 (Control)</th>
<th>Model 2 (Direct)</th>
<th>Model 3 (Full Model)</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>Absolute Deprivation</td>
<td></td>
<td>-</td>
<td>-0.031</td>
<td>-0.229</td>
</tr>
<tr>
<td></td>
<td>GINI</td>
<td></td>
<td>-</td>
<td>-13.348**</td>
<td>-13.792**</td>
</tr>
<tr>
<td></td>
<td>Hispanic/White Unemployment</td>
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<td>-</td>
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<td>-0.168</td>
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<td></td>
<td>Black/White Unemployment</td>
<td></td>
<td>-</td>
<td>-0.349**</td>
<td>-0.219*</td>
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<td></td>
<td>Divorce Rate</td>
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<td>-</td>
<td>0.890***</td>
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<th>Situational Action Theory Components</th>
<th>Structural Predictors</th>
<th>Model 1 (Control)</th>
<th>Model 2 (Direct)</th>
<th>Model 3 (Full Model)</th>
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<td></td>
<td>-</td>
<td>-</td>
<td>0.003**</td>
</tr>
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<td></td>
<td>Black Protestant</td>
<td></td>
<td>-</td>
<td>-</td>
<td>-0.014***</td>
</tr>
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<td></td>
<td>Mainline Protestant</td>
<td></td>
<td>-</td>
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<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>Catholic</td>
<td></td>
<td>-</td>
<td>-</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>Other</td>
<td></td>
<td>-</td>
<td>-</td>
<td>0.007***</td>
</tr>
<tr>
<td></td>
<td>Alcohol-Induced Mortality Rate</td>
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<td>-</td>
<td>-</td>
<td>0.268***</td>
</tr>
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<td>Police</td>
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<table>
<thead>
<tr>
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<th>Structural Predictors</th>
<th>Model 1 (Control)</th>
<th>Model 2 (Direct)</th>
<th>Model 3 (Full Model)</th>
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</thead>
<tbody>
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<td>0.489***</td>
<td>0.387***</td>
</tr>
<tr>
<td>R²</td>
<td></td>
<td>-1.561***</td>
<td>-2.845</td>
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</tr>
<tr>
<td>AIC</td>
<td></td>
<td>5061.860</td>
<td>4891.820</td>
<td>4681.950</td>
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</tbody>
</table>

*: p < .05; **: p < .01; ***: p < .001
6.3. **Association between the Lethal Violence Rate and the Structural Covariates**

The lethal violence rate demonstrates the total amount of lethal. Thus, the association between the lethal violence rate and structural covariates suggests what structural covariates make population collectively express their frustrations in either form of lethal violence. Identical to the previous sections on the homicide rate and the suicide rate analysis, this study first identifies the spatial dependence in contextual predictors and then tests the effects of structural covariates on the lethal violence rate with the three additive spatial regression models.

**6.3.1. Descriptive Statistics on the Lethal Violence Rate and the Structural Covariates**

Table 10 presents bivariate correlations between the rate of lethal violence and other variables. The lethal violence rate is positively and significantly correlated with population age over 65 \((r=0.30, p<0.001)\), gender ratio \((r=0.07, p<0.05)\), divorce rate \((r=0.53, p<0.001)\), combined absolute derivation \((r=0.52, p<0.001)\), Gini coefficient \((r=0.19, p<0.001)\), Evangelical Protestant \((r=0.27, p<0.001)\), Black Protestant \((r=0.27, p<0.001)\), and alcohol mortality rate \((r=0.49, p<0.001)\). In addition, the lethal violence rate is negatively and significantly associated with population age between 20 and 34 \((r=-0.17, p<0.001)\), foreign born \((r=-0.24, p<0.001)\), immigrants \((r=-0.07, p<0.05)\), Hispanic/White unemployment ratio \((r=-0.09, p<0.01)\), Mainline Protestant \((r=-0.13, p<0.001)\), and Catholic \((r=-0.28, p<0.001)\).

Map 4-1 presents that the lethal violence rate is unevenly distributed, with the south having a higher rate of lethal violence than the northern. Counties with a lethal violence rate between 25.4 and 58.0 are concentrated in the southwestern areas, including northern California, Arizona, New Mexico, and small clustered areas in southeastern part. Moreover, as seen in map 3-2, the high levels of lethal violence rate (High-High) are found in the mid-part of the West Coast, including northern California, Arizona, and New Mexico. Lower levels of lethal violence
rate (Low-Low) are found along the New England coastline. These results are similar to the scatterplot map of the suicide rate in map 2-2. This similarity between the two maps may be explained by that the substantial proportion of the lethal violence rate is taken by the suicide rate, rather than the homicide rate. As seen in table 1, the mean for the suicide rate is 15.50 whereas the mean for homicide rate is 6.39 while their standard deviation is similar to each other as 4.75 (homicide rate) and 4.92 (suicide rate).

Map 4-1. Geographic Distribution of the LVR across the U.S. Counties

Map 4-2. Scatter Plot Map of the LVR Based on LISA
6.3.2. **Multivariable spatial regression model for the lethal violence rate**

Table 11 shows the findings from the multivariable spatial regression models for the lethal violence rate. Similar to other dependent variables in the previous sections, this study uses the spatial error model over spatial lag in reference to the LM and the robust LM values.

Model 1 includes control variables and indicates that the population age between 20 and 34 ($b=0.155, p<0.05$) and the population age over 65 ($b=0.560, p<0.001$) are positively and significantly associated with the lethal violence rate whereas foreign born ($b=-0.479, p<0.05$) and immigrants ($b=-0.147, p<0.01$) are negatively and significantly associated. Only the population over 65 remains consistent though model 3. Gender ratio is not found to be statistically significant in model 1, but does become significant in model 3.

In model 2, several socioeconomic predictors are added as direct effects on the rate of lethal violence. Overall, effects of socioeconomic predictors on the lethal violence rate are more similar to those of the homicide rate (table 6) rather than the suicide rate (table 9). Similar to the homicide rate, the lethal violence rate is positively associated with the combined absolute derivation indicator ($b=2.677, p<0.001$) and the Gini coefficient ($b=22.130, p<0.001$). These results are consistent with previous findings of strong and stable associations between lethal violence and not only absolute deprivation (Lee et al., 2008; Wadsworth et al., 2014), but also relative deprivation (Wadsworth & Kubrin, 2007; Wang & Arnold, 2008). Even though both economic indicators are found to have positive effects on the lethal violence rate, the effects of the relative deprivation might be different. As previous sections noted, the combined absolute deprivation indicator and the Gini coefficients are positively and significantly associated with the homicide rate (table 7); the Gini coefficient is significantly associated only in a negative direction. In addition, unlike the homicide rate, the lethal violence rate is positively associated
with the divorce rate \( (b=1.043, p<0.001) \). The significant effects of the divorce rate are consistent with the majority of previous studies, which found relatively stable and positive effects on lethal violence (Pridemore, 2002).

Lastly, model 3 presents the full model incorporating all variables. It is found that Black Protestant \( (b=0.039, p<0.001) \), other religion \( (b=0.007, p<0.05) \), and alcohol-induced mortality rate \( (b=0.334, p<0.001) \) have significantly positive impacts on the lethal violence rate. All other four variables are found not significant. This study finds that in consideration of controlled and mediating effects altogether, there are some dramatic changes in the effects of socioeconomic predictors on the lethal violence rate. The standardized coefficients for the absolute deprivation \( (\Delta b=0.843) \) and divorce rate \( (\Delta b=0.184) \) slightly decrease whereas the coefficients for Gini coefficient becomes not significant \( (\Delta b=14.481) \) (fully mediated). The different coefficients of these three predictors before and after introduction of mediating variables presents that the situational action theory components have substantial indirect effects on the suicide rate (Judd & Kenny, 1981). The proportion of mediating effect for each significant socioeconomic predictor is 23.8% for absolute deprivation and 15.0% for divorce rate. These results suggest the social action theory’s social component indicators, Black Protestant, Catholic, and alcohol consumption indicators mediate the effects of socioeconomic predictors on the lethal violence rate. Based on the results from the three models in table 11, the relationships among all variables are summarized in figure 8.
Table 11. Controlled, Direct, and Mediating Effects on the LVR (Spatial Error Models)

<table>
<thead>
<tr>
<th>Structural Predictors</th>
<th>Model 1 (Control)</th>
<th>Model 2 (Direct)</th>
<th>Model 3 (Full Model)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Controlled Effects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Demographic Features</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (20-34)</td>
<td>0.155*</td>
<td>-0.005</td>
<td>-0.032</td>
</tr>
<tr>
<td>Age (over 65)</td>
<td>0.560***</td>
<td>0.212***</td>
<td>0.114*</td>
</tr>
<tr>
<td>Gender Ratio</td>
<td>5.067</td>
<td>3.698</td>
<td>5.653*</td>
</tr>
<tr>
<td>Foreign Born</td>
<td>-0.497*</td>
<td>-0.426**</td>
<td>-0.262</td>
</tr>
<tr>
<td>Immigrants</td>
<td>-0.147**</td>
<td>0.020</td>
<td>0.029</td>
</tr>
<tr>
<td>Direct Effects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Socio-Economic Status</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Absolute Deprivation</td>
<td></td>
<td>2.677***</td>
<td>1.834***</td>
</tr>
<tr>
<td>GINI</td>
<td></td>
<td>22.130***</td>
<td>7.649</td>
</tr>
<tr>
<td>Hispanic/White Unemployment</td>
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<td>Black/White Unemployment</td>
<td></td>
<td>-0.236</td>
<td>-0.230</td>
</tr>
<tr>
<td>Divorce Rate</td>
<td></td>
<td>1.043***</td>
<td>0.859***</td>
</tr>
<tr>
<td>Mediating Effects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Situational Action Theory Components</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Evangelical Protestant</td>
<td></td>
<td>-</td>
<td>0.002</td>
</tr>
<tr>
<td>Black Protestant</td>
<td></td>
<td>-</td>
<td>0.039***</td>
</tr>
<tr>
<td>Mainline Protestant</td>
<td></td>
<td>-</td>
<td>-0.001</td>
</tr>
<tr>
<td>Catholic</td>
<td></td>
<td>-</td>
<td>-0.001</td>
</tr>
<tr>
<td>Other</td>
<td></td>
<td>-</td>
<td>0.007*</td>
</tr>
<tr>
<td>Alcohol-Induced Mortality Rate</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Police</td>
<td></td>
<td>-</td>
<td>0.334***</td>
</tr>
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<td>Spatial Parameter(Lambda)</td>
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<td></td>
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<td>0.408***</td>
</tr>
<tr>
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<td>-6.880</td>
<td>-3.058</td>
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<tr>
<td>AIC</td>
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<td>0.569</td>
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</tr>
<tr>
<td></td>
<td>5904.300</td>
<td>5531.740</td>
<td>5368.78</td>
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</table>

*: p < .05;  **: p < .01;  ***: p < .001
6.4. Association between the Suicide/Homicide Rate and Structural Covariates

Finally, this study examines the effects of structural covariates on the suicide/homicide rate. The suicide/homicide rate demonstrates which form of lethal violence is most prevalent in a society. As with the other outcome variables, this study first checks the spatial autocorrelation in contextual predictors and then tests their effects on the suicide/homicide rate with three spatial regression models.

6.4.1. Descriptive Statistics on the Suicide/Homicide Rate and Structural Covariates

Table 12 presents bivariate correlations between the suicide/homicide rate and other variables. The suicide/homicide rate is positively and significantly correlated with population age over 65 ($r=0.17$, $p<0.001$), gender ratio ($r=0.15$, $p<0.001$), immigrants ($r=0.16$, $p<0.001$), Catholic ($r=0.14$, $p<0.001$), other religion ($r=0.12$, $p<0.001$), and alcohol mortality rate ($r=0.09$, $p<0.01$). The suicide/homicide rate is negatively associated with population age between 20 and 34 ($r=-0.19$, $p<0.01$), combined absolute derivation ($r=-0.57$, $p<0.001$), Gini coefficient ($r=-0.47$, $p<0.001$), Black/White unemployment ratio ($r=-0.21$, $p<0.001$), Evangelical Protestant ($r=-0.23$, $p<0.001$), Black Protestant ($r=-0.60$, $p<0.001$), and police ($r=-0.19$, $p<0.001$).

Map 5-1 indicates that the geographic distribution of the suicide/homicide rate is far from random. As seen in the map, there are several clustering of the suicide/homicide across the U.S. In particular, counties with the suicide/homicide between 0.815 and 0.949 are concentrated along the coastal areas, including Washington, California, Florida, and southern New England. Additionally, this study examines the suicide/homicide rate with LISA. As seen in Map 5-2, several small clusters of high-level suicide/homicide rate (High-High) are scattered across Oregon, Colorado, Florida, and New England, whereas small clusters of low-level
suicide/homicide rate (Low-Low) are in Louisiana, Arkansas, Georgia, and South and North Carolina. These results indicate when the suicide/homicide rate increases in the High-High counties, it also increases in surrounding counties; however, in Low-Low counties, the low suicide/homicide rate is positively related to low suicide/homicide rates in neighboring counties.

**Map 5-1. Geographic Distribution of the SHR across the U.S. Counties**

**Map 5-2. Scatter Plot Map of the SHR Based on LISA**
6.4.2. **Multivariable Spatial Regression Model for the Suicide/Homicide Rate**

Table 13 shows the findings from the multivariable spatial regression models for the suicide/homicide rate. Similar to the other three outcome variables, this study chooses to use the spatial error model over spatial lag in reference to the LM and the robust LM values.

Model 1 includes control variables and shows that gender ratio \( (b=0.351, p<0.001) \) and immigrants \( (b=0.007, p<0.001) \) are positively and significantly associated with the suicide/homicide rate whereas population age between 20 and 34 \( (b=-0.008, p<0.001) \) is negatively associated with it. Among these three variables, only gender ratio remains significant in model 3. Neither population age over 65 nor being foreign born is a statistically significant predictor of the suicide/homicide rate.

Model 2 examines several socioeconomic predictors. This study finds that four significant variables, combined absolute deprivation indicator \( (b=-0.083, p<0.01) \), Gini coefficient \( (b=-1.155, p<0.0001) \), Hispanic/White unemployment ratio \( (b=-0.008, p<0.05) \), and Black/White unemployment ratio \( (b=-0.008, p<0.05) \), have negative effects on the suicide/homicide rate. The inclusion of socioeconomic variables produce some changes in the demographic feature indicators. Population age between 20 and 34 and immigrants cease to be significant whereas population age over 65 \( (b=0.009, p<0.001) \) and foreign born \( (b=-0.007, p<0.05) \) do become significant. Like the homicide rate, the divorce rate is not found to be significant. This result might be explained by the strong effects of the four other indicators of absolute and relative deprivation (Messner & Tardiff, 1986).

Model 3 presents the full model incorporating all variables. It is found that the alcohol consumption indicator \( (b=0.001, p<0.05) \) is positively associated with the suicide/homicide rate whereas Black Protestant \( (b=-0.001, p<0.001) \) and the number of police officers \( (b=-5.58844e-5) \).
005, $p<0.001$) are negatively associated with it. One interesting finding is that the number of police officers has a negative effect on the suicide/homicide rate even though the strength of impact is not that substantial. This means that counties with more police officers tend to have more residents who resort to homicide instead of suicide when economically frustrated. Considering that police presence has a significant impact on the homicide rate (table 7), but not on the suicide rate, the effects of police presence on the suicide/homicide rate originates from the relationship between the homicide rate and the police.

Some changes occur with the addition of situational action theory component indicators in model 3. The table shows that, in consideration of controlled and mediating effects, the standardized coefficients for combined absolute derivation ($\Delta b=0.014$), Gini coefficient ($\Delta b=0.353$), and Hispanic/White unemployment ratio ($\Delta b=0.007$) slightly decrease while the Black/White unemployment ratio ($\Delta b=0.004$) becomes not significant (fully mediated). The difference of the two coefficients presents the indirect effects of mediating variables (Judd & Kenny, 1981). The proportion of mediating effect for each significant socioeconomic predictor is 3.2% for Gini coefficient, 27.1% for Black/White unemployment ratio, and 13.5% for divorce rate. These results suggest the effects of social action theory’s social component mediate the effects of socioeconomic predictors on the suicide/homicide rate. Based on the results from the three models in table 13, the relationships among all variables are summarized in figure 9.

Table 14 combined all four models for each dependent variable from tables 7, 9, 11, and 13. Table 14 does not provide any new information, but facilitates comparison of different effects of contextual predictors on each dependent variable.
Table 13. Controlled, Direct, and Mediating Effects on the SHR (Spatial Error Models)

<table>
<thead>
<tr>
<th>Structural Predictors</th>
<th>Model 1 (Control)</th>
<th>Model 2 (Direct)</th>
<th>Model 3 (Full Model)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Controlled Effects</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Demographic Features</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (20-34)</td>
<td>-0.008***</td>
<td>0.002</td>
<td>0.001</td>
</tr>
<tr>
<td>Age (over 65)</td>
<td>0.002</td>
<td>0.009***</td>
<td>0.008***</td>
</tr>
<tr>
<td>Gender Ratio</td>
<td>0.351***</td>
<td>0.219***</td>
<td>0.129**</td>
</tr>
<tr>
<td>Foreign Born</td>
<td>-0.002</td>
<td>-0.007*</td>
<td>-0.009**</td>
</tr>
<tr>
<td>Immigrants</td>
<td>0.007***</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td><strong>Direct Effects</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Socio-Economic Status</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Absolute Deprivation</td>
<td></td>
<td>-0.083***</td>
<td>-0.069***</td>
</tr>
<tr>
<td>GINI</td>
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<td>-1.155***</td>
<td>-0.802***</td>
</tr>
<tr>
<td>Hispanic/White Unemployment</td>
<td>-</td>
<td>-0.008*</td>
<td>-0.001**</td>
</tr>
<tr>
<td>Black/White Unemployment</td>
<td>-</td>
<td>-0.008*</td>
<td>-0.004</td>
</tr>
<tr>
<td>Divorce Rate</td>
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<td>0.003</td>
<td>0.003</td>
</tr>
<tr>
<td><strong>Mediating Effects</strong></td>
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<td></td>
<td></td>
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<tr>
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<td>-</td>
<td>3.23791e-05</td>
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<td>Evangelical Protestant</td>
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<td>-</td>
<td>-0.001***</td>
</tr>
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<td>Mainline Protestant</td>
<td>-</td>
<td>-</td>
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<tr>
<td>Catholic</td>
<td>-</td>
<td>-</td>
<td>-2.21647e-05</td>
</tr>
<tr>
<td>Other</td>
<td>-</td>
<td>-</td>
<td>0.000</td>
</tr>
<tr>
<td>Alcohol-Induced Mortality Rate</td>
<td>-</td>
<td>-</td>
<td>0.001*</td>
</tr>
<tr>
<td>Police</td>
<td>-</td>
<td>-</td>
<td>-5.58844e-05</td>
</tr>
<tr>
<td><strong>Spatial Parameter (Lambda)</strong></td>
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<td>0.354***</td>
<td>0.281***</td>
</tr>
<tr>
<td><strong>Constant</strong></td>
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<td>0.858***</td>
<td>0.835***</td>
</tr>
<tr>
<td><strong>R²</strong></td>
<td>0.255</td>
<td>0.570</td>
<td>0.638</td>
</tr>
<tr>
<td><strong>AIC</strong></td>
<td>-1280.120</td>
<td>-1786.490</td>
<td>-1948.990</td>
</tr>
</tbody>
</table>

*: p < .05;  **: p < .01;  ***: p < .001
Table 14. Comparison of All Full Model of HR, SR, LVR, and SHR (Spatial Error Model)

<table>
<thead>
<tr>
<th>Structural Predictors</th>
<th>HR</th>
<th>SR</th>
<th>LVR</th>
<th>SHR</th>
</tr>
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<tr>
<td><strong>Controlled Effects</strong></td>
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<td></td>
</tr>
<tr>
<td>Demographic Features</td>
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</tr>
<tr>
<td>Age (20-34)</td>
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<td>-0.032</td>
<td>0.001</td>
</tr>
<tr>
<td>Age (over 65)</td>
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<td>0.290***</td>
<td>0.114*</td>
<td>0.008***</td>
</tr>
<tr>
<td>Gender Ratio</td>
<td>-2.216</td>
<td>7.681***</td>
<td>5.653*</td>
<td>0.129**</td>
</tr>
<tr>
<td>Foreign Born</td>
<td>-0.037</td>
<td>-0.247*</td>
<td>-0.262</td>
<td>-0.009**</td>
</tr>
<tr>
<td>Immigrants</td>
<td>0.015</td>
<td>0.020</td>
<td>0.029</td>
<td>0.000</td>
</tr>
<tr>
<td><strong>Direct Effects</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Socio-Economic Status</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Absolute Deprivation</td>
<td>2.015***</td>
<td>-0.229</td>
<td>1.834***</td>
<td>-0.069***</td>
</tr>
<tr>
<td>GINI</td>
<td>20.501***</td>
<td>-13.792**</td>
<td>7.649</td>
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*: p < .05;   **: p < .01;   ***: p < .001
CHAPTER 7: DISCUSSIONS AND CONCLUSIONS

7.1. Discussions

Since the emergence of the stream analogy and the frustration-aggression model, several scholars have expanded and integrated the original models with theories drawn from other fields (Andersson, 2015; Browning, 2005; Zhang & Lester, 2008). Aligning with these attempts, this study demonstrates how changes in contextual predictors are reflected differently in changes in homicide rate, suicide rate, lethal violence rate, and suicide/homicide rate. In this process, this study contributes to the theoretical and methodological research on lethal violence. From a theoretical perspective, this study analyzes lethal violence in terms of the social component of situational action theory. The primary objective in incorporating social action theory’s social component is to examine how contextual predictors that influence the propensity for lethal violence mediate the relationship between socioeconomic predictors and lethal violence. Moreover, from a methodological perspective, in contrast to traditional research, this study assumes non-independence of observations in lethal violence and captures it in the model specification. Accordingly, this study utilizes several spatial analysis techniques to consider effects of spatial autocorrelation among contextual predictors.

The results of this study suggest that there is spatial autocorrelation for all types of lethal violence in the U.S. counties and support for the findings of previous macro-level studies (Baller & Richardson, 2002; Messner et al., 1999). These spatial autocorrelations in the outcome variables are demonstrated by the Moran’s I and the LISA statistics (figures 2 through 5 and maps 2-1 through 5-2). The spatial diagnostics presents that the choices of homicide and/or suicide within a county influence those within adjacent counties more than those of counties that are farther away. Taking account of this “contagious” nature of lethal violence (Abrutyn &
Mueller, 2014), spatial effects needs to be considered in testing possible relationships between structural covariates and social phenomena that occur across different geographical units. Consideration of spatial process in macro-level analysis alleviates any possible statistical bias resulting from traditional inferential statistical models that ignore that spatial effect (Baller et al., 2006; Morenoff et al., 2001; Tita & Radil, 2010).

Moreover, the results of this study provide that among all variables, the three contextual variables, including population age over 65, Black Protestant, and alcohol consumption indicator, are significantly associated with all dependent variables as seen in table 14. The alcohol consumption indicator is the only predictor to have a positive impact on all dependent variables, homicide rate, suicide rate, lethal violence rate, and suicide/homicide rate. This interesting finding aligns with those of previous studies identifying the association between per capita alcohol consumption and lethal violence (Miles, 2012; Ramstedt, 2001). The positive effects of alcohol consumption on the lethal violence rate might be natural given that, lethal violence rate is the sum of the homicide rate and the suicide rate.

Concerning the suicide/homicide rate, the results indicate that the greater the alcohol consumption within a county, the more people choose suicide over homicide when facing socioeconomic frustration. These positive effects of alcohol consumption on lethal violence does not solely originate from alcohol consumption per se, but from its interaction with other contextual predictors, such as lack of social control and the divorce rate (Miles, 2012).

In addition, the results associate the percentage of Black Protestant with the homicide rate and the lethal violence rate, but not with the suicide rate or the suicide/homicide rate (table 14). These different effects on each dependent variable might originate from Black Protestants’ own pedagogy shaping their concrete views of political and economic views (Steensland et al.,
According to Steensland et al. (2000), Black Protestants “emphasize different aspects and nuances of Christian doctrine, especially the importance of freedom and the quest for justice,” which “has historically reflected their material and psychological deprivation and their political marginality” (p. 294). These religious doctrines might function as risk factors or protective factors for each type of lethal violence. Alternatively, this significant relationship between Black Protestant and the lethal violence might be affected by unobserved compounding variables that also influence the other two variables—the combined absolute deprivation indicator and the Gini coefficient—which have the same directions with those of Black Protestant in their standardized coefficients.

Additionally, the population over age 65 is negatively associated with the homicide rate, but not for the suicide rate, lethal violence rate, and suicide/homicide rate. The positive association between the elderly population and the suicide rate is consistent with previous studies (Gove & Hughes, 1980; Moore et al.; Recker & Moore, 2016). One interesting result is the negative impact of elderly population groups on the homicide rate. Previous studies have focused on the young population when examining the relationship between age structure and the homicide rate, and most have found a positive association (Marvell & Moody, 1991). The negative effects of elderly population on the homicide rate might be understood as a flipside of positive effects of young population group because it is assumed that a county with a high level of elderly population is more likely to have a smaller young population. However, this explanation might contradict its own results that the effect of population age 20 and 34 predictor is not significant (table 14). Alternatively, beyond age structure itself, age-specific issues, such as economic and relational frustrations, that individuals inevitably and commonly experience at their developmental stages might have confounded the relationships.
Besides these three variables, gender ratio and two economic indicators demonstrate different effects depending on the types of lethal violence. First, absolute deprivation is associated positively with the homicide rate and the lethal violence rate and negatively with suicide/homicide rate. Similarly, the Gini coefficient is associated positively with the homicide rate and the suicide rate and negatively with the suicide/homicide rate. Considering even two predictors’ non-significant effects, such as the combined absolute deprivation for the suicide rate and the Gini coefficient for the lethal violence rate, directions in the effects of the two variables are identical for each dependent variable. These indiscriminate effects of two economic predictors are not consistent with previous findings that individuals become more hostile and aggressive when they perceive themselves deprived only in relation to perceptible reference groups (Messner, 1982; Messner & Tardiff, 1986; Pridemore, 2002).

Lastly, gender ratio has a stable and consistent effect on lethal violence. This predictor is significantly and positively associated with the suicide rate, lethal violence rate, and suicide/homicide rate. It is also found that divorce rate is significantly and positively associated with lethal violence rate and suicide/homicide rate. Lastly, four variables, which are population age between 20 and 34, being an immigrant, and being mainline Protestant or Catholic do not have a significant effect on any of the dependent variables when combined with all other variables (table 14).

7.2. **Policy Implications**

This study found that the structural variables, operating as forces of production and direction, have a disparate effect on different types of lethal violence. From these results, this study concluded that deteriorating SES indicators operate as forces of production. At the same time, almost the same SES indicators, with the exception of the divorce rate, operates as forces
of direction that negatively impact the suicide/homicide rate. This means that faced with economic frustration, counties have more homicides than suicides. These results might indicate that the counties with deteriorating economic indices need to fight against crimes, including homicide, rather than suicide. These efforts might include increasing the number of police officers, setting up more surveillance cameras, and adopting crime prevention policies through environmental design to create safer neighborhoods. These efforts might have been already realized, as evidenced by the findings of this study showing that counties with a high homicide rate tend to have more law enforcement officers.

In addition, this study found that alcohol consumption has a consistent and positive impact on four types of lethal violence. This finding shows that alcohol consumption operates as a force of production and of direction. As several studies have shown, alcohol consumption is a critical risk factor for individual and public health. Thus, counties with a high rate of alcohol consumption needs to adopt an effective alcohol policy, including anti-alcohol campaigns or clinical interventions to improve the collective level of constraint. These efforts or intervention might indirectly reduce lethal violence. However, frustration, mainly caused by deteriorating economic indices, is less likely to be reduced without improving the quality of life or reducing economic inequality. The hostility and aggression built up by perceived relative deprivation can erupt in either homicide and suicide at any time when the social and external constraints fail. Thus, communities need to make additional effort to minimize economic inequality and poverty by raising the minimum wage, investing in early childhood education, and supporting racial integration in the economy and politics (Powell, 2014).

7.3. Limitations

Even though the spatial analysis in lethal violence research has many positive qualities,
there are some limitations in this study. The first limitation is that this study uses a rather large geographic unit—the county—as unit of analysis due to data availability. However, researchers have increasingly used smaller spatial units of analysis that are more likely to have homogeneous structural features within their boundaries (Weisburd et al., 2009). Thus, using the county as unit of analysis might have underestimated lower-order unit variability, which occurs in the census tract or block. Thus, future studies need to consider the possibility of using geographically weighted regression (GWR) models, that can capture variations at the more localized level.

Next, related to the unit of analysis, this study includes only 998 counties that recorded both homicides and suicides over the 5-year period. In other words, this study excluded 2,144 counties that reported no homicides or suicides. Exclusion of almost two-thirds of all counties might reduce the accuracy of statistical inferences. However, in 2016, 270,352,276 people resided in those 998 counties, or 84.86% of the total U.S. population (318,558,162 people). This small number of counties therefore accounts for much of the lethal violence phenomenon in the U.S. On the point of contiguity in the spatial analysis, this small number of counties might an issue. However, as Arbia et al. (2016, p. 180) have pointed out, when the locations of individual counties are perfectly known, but only observations are missing, “this case is a conventional case of missing data,” not a specific issue in the spatial analysis. Still, this missing data can be an issue when “data are missing in clusters in which case entire geographic features, such as spatial spill overs, tend to disappear” (Arbia et al., 2016, p. 188). However, as seen in map 1, in this study the 998 counties tend to cluster along the coastline and connect to each other; the excluded counties tend to cluster in the midwestern U.S. The strong spatial dependence indicated by Moran’s I in lethal violence seen in figures 2, 3, 4, and 5 is evidence of strong contiguity despite the 2,144 counties that are excluded. However, to address this issue, future studies should
consider the possibility of using geographically weighted zero-inflated Poisson model, which accounts for spatial dependence as well as the inflated true-zero issue in variables.

Most datasets were compiled between 2012 and 2016 based on data from the U.S. Census Bureau and the CDC. This study uses 5-year-averaged data for the dependent and independent variables. However, some data sets, such as from the ASARB and the CSLLEA, are compiled in the different time points. These differences between observations could result in imprecise coefficient estimates. In addition, these variables are based on cross-sectional data resources; thus, this study might have overlooked the existence of temporal dependence among variables. There are several advanced statistical tools, such as spatial panel data analysis, which control both spatial and temporal dependence. Thus, future studies need to consider using those tools to increase the accuracy of statistical inferences.

Moreover, there are conceptual limitations in studies of correlations among structural variables (James & Cossman, 2006). One concern is the ecological fallacy, the risk of invalid transfer of result of aggregate analyses to the individual level. Correlations found among structural variables differ from the correlations among similar indicators at the individual level (Gove & Hughes, 1980). Thus, results of county-level analysis need to be interpreted with caution. The structural covariates considered in this study are not exhaustive, but only limited by data availability; thus, future studies of lethal violence should identify and examine additional variables. Other contextual predictors indicating social components of situational action theory can be included in future investigations of lethal violence.

Lastly, the proxy variables, such as the sizes of different religious denominations, used to operationalize the concept of collective morality need to be understood with caution. Even though this and previous studies operationalized the concept of morality in terms of religious
belief or denomination, these variables might not necessarily indicate the morality of a population, but the characteristics of members of a religious denomination. These demographic features of certain religious denominations might be associated with racial heterogeneity indices. This study did not directly measure racial heterogeneity with proportions of each racial group, but only with immigration and nativity, captured with the percentage of immigrants and foreign born. Future studies need to make a distinction between birthplace and ethnicity and examine not only their differing effects on lethal violence, but also their confounding effects with other exogenous variables, including religiosity.

In addition, these possible confounding effects or inappropriate choice of variables might render the mediation model vulnerable because the difference of coefficient approach used in this study is not advantageous in analyzing the indirect effects among multiple mediators with multiple covariates and the causal relationship among variables (MacKinnon et al., 2002). Even though this study found mediating effects of components of situational action theory, such as alcohol consumption, on the relationship between contextual predictors and lethal violence, these mediating effects were relatively weak and were measured without consideration of different pathway. Thus, future studies need to consider the possibility of using structural equation modeling (SEM), which examines the effects among not only observable variables with causal pathway, but also unobservable (latent) variables to impute relationship with observable variables.

7.4. Conclusions

In conclusion, this study illustrates that changes in contextual predictors at the county level are associated with the homicide rate, the suicide rate, the lethal violence rate, and the suicide/homicide rate. The findings in this study are consistent with those of prior contextual
studies of lethal violence.

This study, however, offers two theoretical and methodological improvements over prior research. This study integrates the social components of situational action theory and finds that such structural components mediate the relationship between other contextual predictors and lethal violence. Alcohol consumption, being Black Protestant, and over 65 years of age produce stable effects on all types of lethal violence. Several other economic predictors, absolute and relative deprivation indicators, have strong explanatory power in changes of lethal violence. In addition, by using several geospatial statistical techniques, this study concludes that the geographical distribution of lethal violence is far from random. Spatial process therefore need to be considered in aggregate analyses.
Table 6. Bivariate Correlations between the homicide rate and contextual predictors. (*: p < .05,  **: p < .01,  ***: p < .001)
Table 8: Bivariate Correlations between the suicide rate and contextual predictors. (*: p < .05,  **: p < .01,  ***: p < .001)
<table>
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<th>Other Religious</th>
<th>Wall Telephone Availability</th>
<th>Rank Inequality</th>
<th>Martial Law</th>
<th>Presence of Armed Forces</th>
<th>Implantable Defibrillator</th>
<th>Age (over 65)</th>
<th>Age (20-34)</th>
<th>Gender</th>
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Table 10. Bivariate Correlations between the lethal violence rate and contextual predictors. (*: p < .05, **: p < .01, ***: p < .001)
Table 12. Bivariate Correlations between the Suicide/Homicide rate and Contextual Predictors.

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<th>Predictor</th>
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*p < .05, **p < .01, ***p < .001*
Map 1. Counties Included in Models

Figure 2, 3, 4, and 5. Moran’s I for the HR, SR, LVR, and SHR

Figure 2. Moran’s I for the HR (0.29)

Figure 3. Moran’s I for the SR (0.51)

Figure 4. Moran’s I for the LVR (0.41)

Figure 5. Moran’s I for the SHR (0.34)
Figure 6. Associations between the HR and Contextual Predictors

**Socioeconomic Features**
- Absolute Deprivation ($b=2.658^{***}$)$[0.643^{***}]$
- GINI ($b=34.71^{***}$)$[14.211^{***}]$

**Situational Action Theory Components**
- Black Protestant ($b=0.053^{***}$)
- Alcohol Consumption ($b=0.061^{**}$)
- Police ($b=-0.001^*$)

**Demographic Features**
- Age over 65 ($b=-0.183^{***}$)

*Note.* Coefficient ($b$) represents indirect effects in brackets [ ] and direct effects in parentheses ( ).

Figure 7. Associations between the SR and the Contextual Predictors

**Socioeconomic Features**
- GINI ($b=-13.348^{***}$)$[0.444^{***}]$
- B/W Unemployed ($b=-0.349^{**}$)$[-0.130^{**}]$
- Divorce Rate ($b=0.890^{***}$)$[0.139^{***}]$

**Situational Action Theory Components**
- Evangelical Protestant ($b=0.003^*$)
- Black Protestant ($b=-0.014^{***}$)
- Other Religion ($b=0.007^{***}$)

**Demographic Features**
- Age over 65 ($b=0.290^{***}$)
- Gender ($b=7.681^{***}$)
- Foreign Born ($b=-0.247^*$)

*Note.* Coefficient ($b$) represents indirect effects in brackets [ ] and direct effects in parentheses ( ).
Figure 8. Associations between the LVR and the Contextual Predictors

**Socioeconomic Features**
- Absolute Deprivation ($b=2.677^{***}$)$[0.834^{***}]$
- GINI ($b=22.130^{***}$)$[14.481]$, Fully Mediated
- Divorce Rate ($b=1.043^{***}$)$[0.184^{***}]$

**Situational Action Theory Components**
- Black Protestant ($b=0.039^{***}$)
- Other Religion ($b=0.007^*$)
- Alcohol Consumption ($b=0.334^{***}$)

**Lethal Violence Rate**

**Demographic Features**
- Age over 65 ($b=0.114^{***}$)
- Gender ($b=5.653^{***}$)

*Note.* Coefficient ($b$) represents indirect effects in brackets [ ] and direct effects in parentheses ( ).

Figure 9. Associations between the SHR and the Contextual Predictors

**Socioeconomic Features**
- GINI ($b=-13.348^{***}$)$[0.444^{***}]$
- B/W Unemployed ($b=-0.349^{**}$)$[-0.130^{**}]$
- Divorce Rate ($b=0.890^{***}$)$[0.751^{***}]$

**Situational Action Theory Components**
- Evangelical Protestant ($b=0.003^*$)
- Black Protestant ($b=-0.014^{***}$)
- Other Religion ($b=0.007^{***}$)
- Alcohol Consumption

**Suicide/Homicide Rate**

**Demographic Features**
- Age over 65 ($b=0.290^{***}$)
- Gender ($b=7.681^{***}$)
- Foreign Born ($b=-0.247^*$)

*Note.* Coefficient ($b$) represents indirect effects in brackets [ ] and direct effects in parentheses ( ).
REFERENCES


Brauer, J. R., & Tittle, C. R. (2016). When crime is not an option: Inspecting the moral filtering


impulsivity are stronger in poorer neighborhoods. *Journal of Abnormal Psychology, 109,* 563-574.


Powell, J. A. (2014, November 9). Fed up with inequality? Six policies for a fair and inclusive society. Retrieved from https://www.huffpost.com/entry/fed-up-with-inequality-si_b_5790852?guccounter=1&guce_referrer=aHR0cHM6Ly9oYWFzaW5zdzGl0dXRILmJlcmtlbGV5LmVkdS9zaXgtdG9saWNpZXMtcVkdWNILWVjb25vbWljLWluZXFIYWxpdHk&guce_referrer_sig=AQAAAK4bgZzz5MGjgrXjzeqQHvWx4ApD5PmwLQbhM7SqwM0SEVB31u2AR54zrewQD2zMHxs-CWOop80vM13esxMOJSjzrLfyE1TeendqkCXHek-z8ciZFN6NX5eJ_J1iKbw060X7nLMkvNTIOgc0zv05kJ5x3Yp14gQn5-1Sqq0


equality and rates of inter- and intra-sexual lethal violence: An exploration of functional


