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The Impact Of Deinstitutionalization On Murders Of Law Enforcement Officers

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THE IMPACT OF DEINSTITUTIONALIZATION ON MURDERS OF LAW
ENFORCEMENT OFFICERS

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ABSTRACT

Occupational risk of violent victimization is a serious concern for law enforcement officers. However, there have been virtually no studies that examined the relationship between the incidence of police officer homicide victimization and the deinstitutionalization movement during which large number of persons with mental illness were released back into communities, often without adequate support systems. Research has shown that persons with certain types of mental illness have a greater propensity for violent behavior if they fail to take prescribed medications and/or abuse illicit substances. Since police are most often the first responders to persons with mental illness in crisis, increases in police encounters with such subjects may increase officer risk of injury and death. The present study will test whether or not increases in the number of mental health patients released from psychiatric hospitals is positively associated with murders of law enforcement officers. State-level data on police officer homicide victimization for the years 1972-2003 are used to test this hypothesis. The study takes advantage of a Bayesian-based hierarchical spatio-temporal analysis, a relatively new analytic technique in Criminology, to simultaneously account for spatial autocorrelation across states as well as over time. The results indicate that the change in the hospitalized mentally ill population had no statistically significant effect on the fatal victimization risk for police in general, but showed some temporal variations when a random slope model was employed. Meanwhile, this study finds negative effects of residential stability, residual incarceration rates, and age structure on police homicides, and positive effects of economic deprivation, female headed households, and percent black on the fatal

risks for police. A hot spot of high-risk areas for police consisting of Georgia, Louisiana, Mississippi, and South Carolina is identified by exceedance probability mapping of the estimated relative fatal risks. Elevated residual risks for police due to unmeasured risk factors are found in several southern states, western states, and midwestern states.

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CHAPTER ONE INTRODUCTION

Occupational violent victimization is a serious concern for law enforcement officers because they are more likely to come into contact with unstable populations, face high levels of criminal violence, and work in more unpredictable situations than the general population. Warchol (1998) and Duhart (2001) reported that working as a law enforcement officer has the highest violence victimization risk in the work place among all occupations. The National Institute for Occupational Safety and Health (NIOSH, 2002) research ranked law enforcement officers as second in terms of probability of being murdered during the work hours, which is only lower than that of taxicab drivers. Besides the extremely traumatic experience for victims' families, the severe violent victimization of law enforcement officers has a substantial adverse impact on agencies and local communities. It can lower the morale of victimized officers' colleagues or trigger unnecessary aggressive policing strategies, which, in turn, may damage the trust between police and the public. Therefore, research on the related risk factors of violence against law enforcement officers has received considerable attention. While most police victimization studies focus on the effect of social structural factors, agency practices, and situational contexts, the relationship between the safety of law enforcement officers and deinstitutionalization, a fundamental mental health policy change in the last century, has been ignored.

Until the 1950s, a considerable proportion of people with serious mental disorders received long-term inpatient treatment in large public psychiatric institutions. Since then, however, a large number of hospitalized mentally ill people have been discharged and placed back into communities. The advancement of improved medications for mental illness, more liberal ideological positions towards human rights, and the reformation of the health care system are believed to have contributed to this change (Gronfein, 1985; Issac & Armat, 1990; Markowitz, 2011; Mechanic & Rochefort, 1990). The original goal of this movement was to free mentally ill patients from highly restrictive facilities and shift the treatment responsibility to community-based programs, thus helping them recover and reintegrate into the community (Mechanic & Rochefort, 1990). This trend, referred to as the deinstitutionalization movement, however, may have had an impact on the occupational risks for law enforcement officers.

Empirical research has revealed that people with certain types of mental illnesses have an increased propensity towards violence compared to non-mentally ill individuals, especially when they exhibit psychotic symptoms or antisocial personality traits, resist treatment, abuse illicit substances, and experience stressful life events (Harris & Lurigio, 2007; Link, Andrews, & Cullen, 1992; Monahan, 1992). In addition, alternative community-based mental health care services, suffering from flawed designs and insufficient funding, often fail to meet the treatment needs of people with mental illnesses, especially those with the aforementioned characteristics (Mechanic & Rochefort, 1990; Torrey, Kennard, Eslinger, Lamb, & Pavle, 2010). As a result, the U.S. has witnessed dramatically increasing crime rates among the mentally ill persons due to their untreated illnesses and life survival needs (Harris & Lurigio, 2007; Hiday, 1997; Nederlof, Muris, &

Hovens, 2013). Meanwhile, the rise of quality of life and zero-tolerance policing drove the criminal justice system to take more aggressive actions against persons with disruptive behaviors and minor offenses (Goldstein, 1990; Wilson & Kelling, 1982). All of these factors significantly increased law enforcement officers' chances of encountering persons with mental disorders (Steadman, Barbera, & Dennis, 1994; Teplin, 1984).

Rising numbers of contacts between police officers and mentally ill persons in crisis have raised police administrators' concerns about the heightened risk of injury and fatalities among officers (Treatment Advocacy Center, 2005). Law enforcement personnel generally perceive situations which involve dealing with mentally ill individuals as some of their most dangerous encounters with the public (Margarita, 1980; Treatment Advocacy Center, 2005; Ruiz & Miller, 2004; Watson, Corrigan, & Ottati, 2004). Despite widespread concerns, the possible elevated safety risk for police due to increases in encounters with mentally disturbed people is surprisingly understudied in the academic literature. Furthermore, the few extant empirical studies provide limited and inconsistent evidence regarding this issue. There have been descriptive reports which showed that police officers are at a higher risk of being injured or killed by mentally ill persons in crisis (Brown & Langan, 2001; Treatment Advocacy Center, 2005). Kaminski (2007) found a significant positive association between the rates of releasing mentally-ill patients and the numbers of the police slain after controlling for some socio-structure variables. However, some other empirical studies concluded that victimizations of officers during police calls involving mentally disrupted people are very infrequent occurrences (Kaminski, DiGiovanni, & Downs, 2004; Kerr, Morabito, & Watson, 2010; Kesic, Thomas, & Ogloff, 2013), and that encounters with the mentally ill, per se, do not

increase the likelihood of casualty for law enforcement officers (Morabito & Socia, 2015).

The inconsistency and relative lack of research in this area may, in part, be due to some methodological obstacles: (1) Some measurement issues make accurate measurement of the interaction between police and people with mental illness very difficult. For example, the misclassification of mental-illness related contacts is not uncommon because officers often cannot accurately identify the mental status of subjects in short encounters. Also, the measurement of officers' responses and related contextual variables in police-citizen contacts suffers from substantial reporting or recording biases (see the discussion in Alpert, 2015). (2) There is no generally accepted measurement of the safety risk for police officers. A handful of existing police safety studies have used officers' perceptions of threats, serious assaults against police, injury incidents, and the murders of officers to measure the violence against police. All of them have some accuracy and/or reliability issues. The difference in the measurement of outcome leads to inconsistent findings. (3) Data is scarce because serious assaults, injury, and the death of officers are rare events in police encounters with the public (Kerr et al, 2010; Kesic et al., 2013). Consequently, the rarity of observations makes meaningful analysis very difficult. A common solution to this problem is aggregating rare events across space and over time to yield enough observations (Woodall & Driscoll, 2015), which also increases considerable spatial and/or temporal variations into the data. However, geographical and time-series autocorrelations exist in these variations. Ignoring such autocorrelations will result in misleading findings. Unfortunately, traditional quantitative methods cannot easily handle such variations at the same time. (4) Even after controlling for a

considerable number of risk factors, many other potential factors, such as unmeasurable local social-structural characteristics, available community-based resources, agency response strategies, and regional subcultures, may have effects on the safety risk for the police. These variables are usually difficult to measure or observe, thus difficult or impossible to control for. This issue also contributes to conflicting findings.

Therefore, to explore whether deinstitutionalization heightens the safety risks for police officers, research is needed that is conducted with enough observations, robust measurement, and a flexible statistical technique amenable to spatial and temporal dependences. Also, a mapping strategy, which maps the estimated risks of police murders after taking into account the effect of measurable risk factors, can help discern residual trends or patterns in the outcome due to latent unmeasurable variables.

The present study aims to fill this gap in the literature by using state-level pooled time-series data of homicides of police officers and the population of psychiatric inpatients over a 32-year period to examine the impact of deinstitutionalization on officer safety, as well as the effects of social structure risk factors after taking temporal and geographical autocorrelations into account. I plan to answer the following research question: Did deinstitutionalization increase the levels of violence against law enforcement officers?

In this study, felonious killings of police, which are one of the most serious adverse consequences of police-citizen encounters and suffer from minimal measurement error, are adopted as an indicator of the level of violence against the police. The state-level annual change in institutionalized populations is chosen as the main independent variable. This variable reflects the pace and extent to which psychiatric inpatients have been

released into communities, thus representing the impact of deinstitutionalization.

According to the research question above, the hypotheses to be tested are:

H₀: Increases in the number of mental health patients released from psychiatric hospitals are not associated with murders of law enforcement officers.

H₁: Increases in the number of mental health patients released from psychiatric hospitals are positively associated with murders of law enforcement officers.

This study uses state-level pooled time series data to examine the relationship between changes in state-level mental health inpatient populations in state and county psychiatric hospitals and changes in the number of police officers murdered. The present study takes advantage of a Bayesian-based hierarchical spatio-temporal analysis approach, a relatively new analysis technique in Criminology, to account for the variations and autocorrelations in time and space (Knorr-Held & Besag, 1998). By using this modelling technique, some smoothing strategies, which involve borrowing the strength from the adjacent time or space units, can be easily applied to solve spatial and temporal dependence issues simultaneously. Such an approach can also provide more accurate risk estimates in rare event data, where observations with extreme values could have a strong impact in zeroes or low count dominated data. A mapping of the estimated risks of police murders, after controlling for the impact of deinstitutionalization and other important exposure variables, can produce a clear visual reflection of the distribution of victimization risks for police, and help discern possible residual patterns due to unmeasured risk factors.

This study is important for several reasons: First, this study can provide information about whether deinstitutionalization increased the occupational risks of officers, and if so,

to what extent, after controlling for some key observable risk factors and temporal/spatial dependence. In doing so, the present study will contribute to the literature regarding the impact of deinstitutionalization on the justice system. Also, it will provide a deep understanding of the factors associated with law enforcement officer homicide victimization. Moreover, this study may reveal certain spatial or temporal patterns of the risk for police after controlling for the impact of deinstitutionalization and important risk factors. Such patterns are caused by residual unmeasured risk factors and may suggest directions for future research. All of these may have important policy implications regarding remedying policy inefficiency, developing effective response programs, allocating prevention resources, and improving police services.

This dissertation proceeds as follows. Chapter 2 opens with a brief introduction and comments on deinstitutionalization, followed by an examination of the empirical evidence pertaining to the violent tendencies of persons with mental illnesses. Chapter 3 explores the interaction between the police and persons with mental illnesses, including arrest, the use of force, and associated safety issues during police encounters with the mentally ill, followed by a discussion of the methodological limitations of the related research. Chapter 4 provides a review of police homicide research. The mixed findings in this field and the possible reasons for this are discussed. Chapter 5 describes the data collection and analytic strategy for this research. Chapter 6 records the process of the analyses and reports the relevant findings. Finally, Chapter 7 closes the dissertation with a discussion of the findings, policy implications, and possible improvements for future research.

CHAPTER TWO

DEINSTITUTIONALIZATION

2.1 BRIEF HISTORY OF DEINSTITUTIONALIZATION

Deinstitutionalization refers to a movement which released long-term inpatients from state mental health institutions to community based services. For a long time, people with serious mental disorders were perceived as extremely dangerous, hence the majority of them were confined to specially designed hospitals for lengthy periods of time. After World War II, environmental determinism and egalitarian notions were widely adopted, and the function of such lengthy inpatient institutions was questioned (Grob 1987; Mechanic, 1989). In his founding work during deinstitutionalization, Foucault (1965, pp. 38-64) claimed that the hospitalization of people with mental disorders, which represents the power of the mainstream population over the marginal members of society, was actually a part of what he called the “Great Confinement”. In this process, people with mental disabilities, unlike those with physical disabilities, were treated as sinful individuals, and were condemned and confined. With horrible care conditions and lengthy separation from society, the psychiatric hospitals in the pre-deinstitutionalization era provided little treatment and rehabilitation, but functioned as incarcerating and punishing institutions (Foucault, 1965). Also, in the mid-1950s and early 1960s, studies demonstrated that long term hospitalization of mentally ill patients reduced their ability to reintegrate back to society (Belknap 1956; Goffman 1961). Meanwhile, the introduction of new medications (i.e., Phenothiazines), which can control a patient’s psychiatric

symptoms more effectively and thus reduce their need of highly coercive administrative actions, made it possible to transfer those long-term institutionalized mentally ill patients from large state hospitals to less restrictive community-based health service programs (Mechanic & Rochefort, 1990; Raphael & Stoll, 2013). As a result, civil rights advocates, mental health staff and patient families called for releasing many mentally ill patients from institutions to community based services. This was the initial ideological motivation for deinstitutionalization (Mechanic & Rochefort, 1990). The 1950s was recognized as the beginning point of the movement for deinstitutionalization. The inpatient population started to decline after it reached a historically high record of 559,000 in 1955 (Morrissey, 1989). At the beginning, the speed at which the mentally ill patients were leased was very slow. Gronfein (1985) reported that the state and county hospital inpatients dropped at an annual rate of only 1.75% from 1955 to 1965.

However, ensuing legislative activities and the expansion of an array of welfare programs fueled this process significantly over the following two decades. The 1963 Community Mental Health Centers Act, (which embodied mental health professionals' faith and confidence in community based service), created a new type of facility known as a community mental health center in order to meet the treatment needs of mentally ill patients (Foly & Sharfstein, 1983; Mechanic & Rochefort, 1990). Therefore, the establishment of community care systems provided a theoretical parallel alternative to the traditional state hospital system. In addition, the introduction of Medicare and Medicaid programs in the 1960s promised that the federal government would share 50% of the cost of nursing homes with states, provided that states were strongly motivated toward transferring mental health patients from state institutions into nursing homes. Moreover,

the expansion of welfare housing projects and disability insurance policies made it easier for mental health patients to move back into communities. Morrissey (1982, 1989) described this situation as “opening the back door” of the state hospitals to release inpatients into alternative mental health care services.

During the 1960s and 1970s, in the wake of the civil rights revolution, the human rights of the mentally ill drew society’s attention and became a focus of fierce debates. Several historical cases notably accelerated the deinstitutionalization movement. In the case of *Jackson v. Indiana* (406 U.S. 715, 1972), the U. S. Supreme Court determined that involuntarily committing a charged criminal offender for an indefinite period solely on the basis of his permanent incapacity to stand trial violates his right to equal protection. In 1975, the decision of the U.S. Supreme Court in *O’Conner vs. Donaldson* (422 U.S. 563), which is viewed as a landmark victory in protecting the civil liberties of individuals with mental illness, ruled that involuntarily commitment of a mentally ill patient is unconstitutional as long as he or she is not imminently dangerous to him- or herself and/or others (also see *Lessard v. Schmidt, E.D. WIS*, 1974). Through *Addington v. Texas* (441 U.S. 418, 1979), the U.S. Supreme Court raised the standard of proof regarding committing individuals for mental health treatment from the usual civil level of “preponderance of the evidence” to a higher “clear and convincing evidence” level. In the following years, in order to be accordant with the decision of the U.S. Supreme Court, civil commitment laws in most states were modified to set very high criteria for involuntary commitment making it very difficult to hospitalize adult patients involuntarily. The higher criteria of involuntary civil or criminal commitment for the

mentally ill persons functioned as “closing the front door” of state facilities (Morrissey, 1982, 1989).

Driven by strong economic incentives and more liberal political views, the rates of deinstitutionalization accelerated dramatically during 1965 to 1980 (Gronfein 1985). The aggregate decreased percentages for residential populations were 29.0% for 1965-1970, 42.7% for 1970-1975, and 31.7% for 1975-1980, in comparison to 4.2% for 1955-1960, and 11.3% for 1960-1965 (Mechanic & Rochefort, 1990). The number of resident patients in the mid 1980’s dropped to about 110,000, an accumulated 81% decrease since the 1950s (Morrissey, 1989). This period is viewed as the “radical phase” of the deinstitutionalization movement (Morrissey, 1982, 1989). After about two decades of aggressively discharging the mental inpatient population and hastily closing state institutions, the psychiatric beds available in state hospitals had reached a very low number (Rapheal & Stoll, 2013). Since the 1980s, deinstitutionalization has continued, though at a visibly slower speed than before. A recent estimate of the current hospitalized population was about 60,000, with only one psychiatric bed available for every 3,000 Americans (Rapheal & Stoll, 2013; Torrey et al., 2010).

While inpatient populations in state hospitals kept shrinking, many other alternative institutions took the responsibility of treating mentally ill persons. Many general hospitals opened to accept patients with mental health problems and have been the main facilities to deal with psychiatric emergency cases (Kiesler & Sibulkin 1987). Between 1965 and 1980, general hospitals saw a six-fold increase in mental health inpatient episodes. In contrast, nursing homes mainly provided service for chronically mentally ill individuals. Linn and Stein (1989) estimated that 30-75% of the patients in nursing homes had mental

disorders. To meet the treatment needs of persons with mental illness a host of community-based services, such as halfway houses, supervised apartments, and board-and-care homes, were developed. Private psychiatric hospitals, making up a very small proportion of the service providers, also saw a dramatic increase in this period (Kiesler & Sibulkin 1987).

Raphael and Stoll (2013) argued that the demographic characteristics of state inpatient populations may vary at each stage of deinstitutionalization. According to the Public Use Microdata Samples (PUMS, 1955-1996), at the beginning of deinstitutionalization, the hospitalized population tended to be older (about 70% were over 40 years old), gender balanced (47.5% female), and predominantly white (87.6%). As the movement pushed forward, those who were considered less of a public safety concern, or those who had better community support resources, e.g., the elderly /female/mainly white patients, constituted the majority of the first wave of those released. As a result, the hospitalized population contained more male, younger, and more racially diverse patients. At the end of the 1980s, the proportion of those aged over 40 in this population shrank to less than 50%, the percentage of males reached 60%, and non-whites made up 21.6% of the total inpatient population (Raphael & Stoll, 2013). When deinstitutionalization progressed to the “radical” stage, more inpatients were rapidly discharged to the community due to liberal political motivations and budget saving orientations, but with less concern about the welfare of patients and safety of the public. This led to a younger, more male, and minority-predominate discharged population. This change, plus the fact that long-term inpatient care was less common for newly diagnosed patients with serious mental illness, altered the clinical characteristics of

the chronic mental illness patient population (Schwartz & Goldfinger, 1981). Unlike the patients in the first discharge wave, the new generations of patients with serious mental illness live in communities, experience more transient living conditions, have less family or community support, show poorer reality testing under stress, and exhibit more anger and impulse control problems. These characteristics, combined with shorter or no inpatient treatment experiences, made this new generation of patients more likely to refuse to accept the idea that they had mental disorders and needed to be treated, thus resisting the continuation of medication (Test, Knoedler, Allness, & Burke, 1985; Schwartz & Goldfinger, 1981). Also, when they feel the pressure of stress, they are more likely to resort to substance abuse, which further exacerbates their mental status (Mechanic & Rochefort, 1990; Pepper, Ryglewicz, & Kirschner, 1982; Sheets, Prevost, & Reihman, 1982).

2.2 DEINSTITUTIONALIZATION AS A POLICY FAILURE

Although deinstitutionalization was a successful movement in terms of freeing millions of mental health patients from intensively restrictive institutions, this mental health policy has repeatedly come under strong criticism since first emerging in the 1950s. Opponents claimed that deinstitutionalization was one of the biggest major public policy failures in US history (Dear & Wolch, 1987; Mechanic & Rochefort, 1990; Torrey et al., 2010). Torrey and his colleagues (2010: 2) commented that deinstitutionalization was “the most well-meaning but poorly planned social changes ever carried out in the United States.”

Many critics focus on the inadequate function of the community mental health care system which was supposed to take responsibility for the treatment for those discharged

from state hospitals. Although non-traditional community supportive services proliferated greatly during the 1960s and 1970s, it would be an overstatement to say that these alternative programs sufficiently replaced the treatment function of traditional state hospitals. Generally, community facilities lack the ability to manage a large numbers of uncooperative mentally ill patients (Torrey et al., 2010).

Recall that the population released into the community during the radical period of the deinstitutionalization movement was younger, more male, and more racially diverse. Shorter hospitalization stays, the stigma of discrimination, and the demographic characteristics of these individuals often made some of them deny the mental illness they had (Pepper et al., 1982; Sheets et al., 1982). Therefore, this sub-population appears to be less cohesive to community based therapy. Once medication was discontinued by choice, their mental status could deteriorate quickly and they might lose the ability to seek treatment and medication voluntarily (Torrey et al., 2010). In addition, the high prevalence of co-occurring substance abuse exacerbated their situation to a larger extent (Harris & Lurigio, 2007; Link et al., 1992; Monahan, 1992; Steadman et al., 1998; Swanson, Borum, Swartz, & Monahan, 1996). As Belcher (1988: 90) explained, “psychotropic medications had been prescribed upon their discharge from the state hospital, but the respondents failed to take their medication and instead chose to self-medicate with alcohol and street drugs.” These persons often exhibited aggressive behaviors and hostile attitudes toward surrounding persons, thus posing safety threats to others and frightening members of the community. In this context, most of the community health services lacked the willingness, ability, and authority to handle this group of dangerous patients. As a result, these dangerous people often remained untreated

in the community, until being captured by the criminal justice system for their criminal behaviors (Engel & Silver, 2001; Novak & Engel, 2005).

Another factor restricting the effect of community-based treatment programs is the long existing shortage of funding. The pace of the investment in community services could not keep up with the increase of the number of mentally ill patients in need. Community mental health care programs have never received enough financial attention. Whenever federal and state governments face fiscal strain, the budget for welfare programs are cut, which affects various forms of community health services. The most distinguished example is that during the Regan administration, the funding for an array of welfare programs, including community mental health services, was substantially slashed (Curtis, 1986). The insufficient financial support directly decreased community treatment facilities' ability to treat, monitor, and counsel persons in mental health crisis (Mechanic, & Rochefort, 1990). Furthermore, significant spending cuts induced tightened eligibility criteria for other welfare programs, such as Medicaid, public housing and disability benefits, and pushed many of the mentally ill persons out of these social programs (Curtis, 1986). This change eroded the subsistence basis of the community service system, downgraded the living conditions of many mentally ill patients, and created more homeless people with mental illness. Since they lacked the ability to change this negative situation compared to normal people, persons with mental illness were more vulnerable to the degradation of their housing environment and economic poverty. These stressful life events could easily trigger the relapse of the disease, making those people lose insight in being able to recognize their disease and to seek therapy. Their lack of willingness to treat their diseases diminished their chances of recovery, which in turn exacerbated their

existing economic difficulties. This is a vicious circle. As a result, some patients could exhibit violent tendencies under the influence of active symptoms. In addition, even mental illness patients who were not violent by nature, occasionally could commit non-violent crimes to obtain essential items for survival (i.e., shop lifting) (Hiday,1997). Either way, these people would eventually encounter the criminal justice system.

As a result of such increasing involvements with the criminal justice system, many persons with mental illness were arrested, tried, and incarcerated. In the recent decades, tough-on-crime approaches (e.g., mandatory minimum sentencing, three strikes laws, and war on the drugs--See the discussion in Fellner, 2006) adopted to respond to the high rising crime wave made the situation worse for mentally ill offenders. There is a disproportionate number of mentally ill people present in jail and prisons (Steadman, Barbera, & Dennis, 1994; Teplin, 1984). Research suggested that incarceration rates are closely related to the changes in the psychiatric institutionalized population. The incarcerated population and the psychiatric inpatient population showed exactly opposite trends. Palermo, Smith, and Liska (1991) found that a significant negative linear Pearson Product-Moment correlation existed between the sizes of these two populations (Correlation Pearson =-.4~.5). Some scholars argued that this is the result of the transinstitutionalization from mental hospitals to correctional facilities. Raphael and Stoll (2013) estimated that deinstitutionalization was responsible for 4%-7% growth in the prison population for the years 1981-2000.

In short, although the original intention of deinstitutionalization was good, its implementation has been considered a policy failure by many scholars. Given the shortage of funding and the changes in the characteristics of the mentally ill population,

the alternative community-based mental health service did not effectively replace the treatment function of state psychiatric hospitals. The shrinking of social welfare programs made this situation worse. Many persons with mental illness might show aggressive behavior or commit petty offenses due to their untreated symptoms and/or their disadvantaged economic conditions, increasing their chances of interacting with the criminal justice system. To some extent, deinstitutionalization simply drove many of the mentally ill from the psychiatric institution into the criminal justice system. A considerable portion of the mentally ill did not truly benefit from deinstitutionalization, but ended up suffering from their inadequately treated diseases and receiving punishment from the criminal justice system.

2.3 ELEVATED VIOLENCE RISK OF THE MENTALLY ILL

Are mentally ill people more violent than the general population? This question is especially important to the criminal justice system in the post-deinstitutionalization era, because heightened violence levels among persons with mental illness will eventually increase their involvement with the justice system, which requires developing specific strategies to handle this population appropriately.

Although persons with mental illness have been perceived as violent and dangerous throughout the ages and across cultures (Monahan 1996), serious exploration of the relationship between mental disorders and criminal behavior did not begin until the middle of the nineteenth century (Harris & Lurigio, 2007; Nederlof et al., 2013). Early studies indicated that persons with mental illness are no more prone, or are even less likely, to be involved in criminal acts than ordinary people (see Ashley, 1922; Cohen & Freeman 1945; Pollock, 1938). These findings were viewed as primary evidence to

support the claim that persons who are mentally ill are no more dangerous than persons in the general population, which became one theoretical basis for the movement of deinstitutionalization. However, the lack of control groups, the relatively small sample sizes, short follow-up periods, and the fact that the majority of the most dangerous mentally ill patients were indefinitely locked in the hospitals, cast huge doubt over the findings and conclusions of these studies. Even within these pre-deinstitutionalization studies, contradictory findings existed (e.g., Brill & Malzberg, 1962).

When the United States entered into the era of deinstitutionalization, more studies revealed a positive relationship between mental illness and criminal acts. Consistent findings showing a heightened tendency for violence among the mentally ill persons were reported from 1965 through 1980 (Durbin, Pasewark, & Albers, 1977; Giovannoni & Gurel's study, 1967; Rapoport & Lassen, 1965; 1966; Steadman, Coccozza, & Melick, 1978; Zitrin, Hardesty, Burdock, & Drossman, 1976). This period is viewed as the rapid stage of the deinstitutionalization movement where a vast amount of patients were discharged from state hospitals into communities. Coccozza and colleagues (1978) attributed this change to the increased number of patients with previous criminal records, and implied that it could be the outcome of "the changing clientele of state hospitals."

Still, some argued that the link between mental illness and criminal acts is doubtful because most aforementioned studies did not consider the effect of the criminalization of people with mental illness which artificially shunts more mentally ill persons into the criminal justice system, or because these studies ignored the influence of many sociodemographic and community context characteristics which are also risk factors for the general public (see Monahan & Steadman, 1983; Link et al., 1992). However, even

with more robust research designs (e.g., longer follow up cohort studies, self-reported measures of violence) and multivariate statistical techniques, the majority of research since the 1980s continues to yield solid evidence of a positive correlation between mental disorders and a propensity for violence.

Using data from the National Institute of Mental Health's Epidemiological Catchment Area Study (ECA), Swanson and colleagues (1990) examined the risk of committing violent acts in a representative sample of adults living in three large cities. Controlling for several relevant factors, they found that self-reported violent acts within the preceding year were 5 times higher among those diagnosed with mental disorder(s) by a psychiatric assessment based on the Diagnostic Interview Schedule than among those who were not. Also, they reported that a significant interaction effect exists between mental disorders and substance abuse. Another study (Link et al., 1992) compared several official recorded and self-reported violent behaviors among 232 former mental patients and 521 people who resided in the same community but without a treatment history. After controlling for the influence of sex, age, race, and local social structure factors, persons with mental illness still had higher rates for a variety of violent behavior than non-patients, either measured by arrests or self-reported behaviors. Additionally, Swanson and colleagues (2006) examined the self-reported violent behaviors among 1,410 subjects from 24 states diagnosed with schizophrenia and related psychoses, the most common forms of serious mental illness. This study showed that 19% reported violent behaviors during the six-month follow-up period, which is much higher than that for the general public (2%).

Further research also tried to probe the mechanisms of the tendency for violence among the mentally ill population. Some researchers believe that this tendency comes from mentally ill persons' specific psychiatric symptoms. Link et al. (1992) found a positive association between violent behaviors and mental illness. They also reported that the seriousness of psychotic symptoms (i.e., hallucinations, delusions) were correlated with the level of violent behaviors. Similarly, based on a survey of 10,066 respondents in three U.S. metropolitan areas, Swanson and colleagues (1996) found that the probability of engaging in violent events for people who had a mental disorder involving paranoid psychotic and delusional characteristics were five times that for normal persons. Recent studies also suggested that certain "positive" or "threat control/override" symptoms are responsible for the mentally ill's aggressive behaviors. Persons with these symptoms accept their hallucination and/or delusions as real, feel threatened by the surrounding environment, are hypervigilant, and may often misunderstand other's actions, thus reacting irrationally, aggressively and violently (Link & Stueve, 1994; Link, Phelan, Bresnahan, Stueve, & Pescosolido, 1999). Notably, after controlling for the seriousness of psychotic symptoms, Links et al. (1992) found that the difference in violent tendencies between the mentally ill and general people markedly diminished. This finding suggested that violence could be more associated with the severity of specific psychotic symptoms than the mental disorder itself. In addition, Swanson et al. (1997) noted that being untreated or inadequately treated is an important risk factor for violent acts in individuals with mental illness. Most recent studies are in accordance with this finding (Alia-Klein, O'Rourke, Goldenstein, & Malaspina, 2007; Elbogen, Van Dorn, Swanson, Swartz, & Monahan, 2006; Swanson et al., 2002). After analyzing the data from 110 studies in a

meta-analysis, Witt, Van Dorn, and Fazal (2013) concluded that not taking medication and non-adherence with therapies were associated with elevated risks of violence among people with psychosis. The above empirical studies strongly imply that the risks of violence in persons with mental disease have a close relationship with their active symptoms and thus could be reduced by adequate and continuing treatment.

Also, strong evidence supports the idea that persons with mental illnesses are more violent when they abuse alcohol or illegal drugs (Steadman et al., 1998; Swanson et al., 1996; Swanson et al., 1997). Abuse of alcohol and illegal drugs may boost violence for individuals with mental disorders in different ways. First, violence could be induced by alcohol and other drugs' direct pharmacological effect (Swanson et al., 2008). Second, mentally ill patients' substance use may compromise the effects of their medication and exacerbate their symptoms, hence making them more violent (Volavka & Swanson, 2010). In addition, substance abuse could decrease treatment compliance in persons with mental illness, which is an important factor in reducing the risk of violence (Volavka & Citrome, 2008).

Finally, mental illness decreases patients' ability to adapt to negative living conditions, making them more vulnerable to stressful life events. When psychiatric patients meet life crises, they generally show poorer emotional management than others, and are thus more likely to respond in violent ways (McNiel, Binder, & Robinson, 2005; Silver & Teasdale, 2005). Using data from the Epidemiological Catchment Area Surveys at the Durham site, Silver and Teasdale (2005) showed that stressful life events and impaired social support can explain a substantial portion of the association between mental illness and violent behaviors. Collecting data on 2,294 individuals in San

Francisco in 1997, McNiel and colleagues (2005) reported that being homeless correlated with increased violence among persons that were mentally ill.

In summary, existing empirical studies have shown a robust positive relationship between persons with serious mental illness and violent tendencies. The findings were not influenced by whether the studies were longitudinal or cross-sectional, whether the researchers used official data or self-reported data, nor whether the violent outcomes included arrest, conviction, or just undocumented aggressive behavior. These findings indicate that heightened levels of violence among a subset of the mentally ill persons in the post-deinstitutionalization era is a fact instead of a stereotypical perception. A greater propensity for violence among some mentally ill inevitably increases their involvement with the criminal justice system. However, it is important to point out the propensity for violence among persons with certain types of mental illness is apparently due to a failure to treat persons with active psychotic or other symptoms, rather than the mental disease itself. Thus, adequate and continuing treatment can substantially reduce the risk of violent behavior (Elbogen et al., 2006; Swanson et al., 1997). In addition, substance abuse, and stressful life events (e.g., unemployment, homelessness) are also contributing factors associated with increased violence among the mentally ill (Silver & Teasdale, 2005).

CHAPTER THREE

INTERACTIONS BETWEEN POLICE AND PERSONS WITH MENTAL ILLNESS

The above discussion established that persons with certain types of mental illnesses who go untreated or fail to take their medications, abuse illicit substances, face adverse life events, etc., have a greater propensity for committing a variety of crimes. Hence, there is a remarkable increase in contacts between persons with mental illness and the criminal justice system. As the gatekeepers of the criminal justice system, law enforcement officers are typically the first responders whenever those mentally ill people act out in the community. This chapter discusses the two competing theories regarding police's response patterns to mentally ill subjects in a post deinstitutionalization context, provides a literature review of related topics, and comments on the methodological obstacles and possible solutions in safety risk research.

3.1 POLICING PERSONS WITH MENTAL ILLNESS: CRIMINALIZATION OR PSYCHIATRIC FIRST AID?

Policing persons with mental illness has been a serious concern of police management since at least the 1960s (Ruiz & Miller, 2004; Treatment Advocacy Center, 2005). As a result of the deinstitutionalization movement, many mentally ill persons locked in long-term psychiatric hospitals have been released into communities since the 1950s. However, financial support for alternative community-based mental health services has always been limited, and therefore many persons with mental illness live in communities with few treatment options. (Borum, Williams, Steadman, & Morrissey,

1998). As noted above, failure to treat and other factors increase the propensity of persons with certain types of mental illness to become violent. Also, the economic poverty induced by their mental disability could drive mentally ill persons to commit more non-violent property crimes to survive (e.g., shop lifting) (Hiday, 1997). In the meantime, the wide adoption of quality of life policing urges police officers to take aggressive actions on petty public disorders and minor offenses (Wilson & Kelling, 1982). Valdiserri, Carroll, & Hartl (1986) found that people with mental disorders have a significantly higher probability of being charged with minor misdemeanor behaviors, such as trespassing and harassment, than individuals without psychiatric problems. Torrey et al. (2010) recorded a case where an individual with mental illness was arrested over two hundred times for repeated petty offences. Torrey et al. (2010) also noted that minor breaches, e.g., traffic violations, disorderly behaviors, and trespassing are the most common causes for mentally ill persons to be picked up by police in Sedgwick County, Kansas. In any case, with the rising population of mentally ill persons in the general community, the chance of police officers encountering mentally disturbed persons increases dramatically (Mechanic & Rochefort, 1990; Torrey, 1997). For example, the number of mentally disturbed individuals taken by the NYPD to hospitals for psychiatric evaluation increased from about 1,000 in 1976 to approximately 25,000 in 1998 (Bumiller, 1999; Torrey, 1997). It was estimated that 6%~10% of police-citizen contacts involved persons with mental illness (Deane, Steadman, & Borum, 1999; Engel & Silver, 2001; Johnson, 2011; Novak & Engel, 2005; Teplin, 1984). Consequently, handling mentally ill individuals has become a regular part of a police officer's daily job (Bittner, 1967; Teplin & Pruett, 1992).

There are two competing hypotheses regarding how police respond to increased encounters involving mentally ill suspects. The first one is the “criminalization” hypothesis (Abramson,1972), which claims that police are inclined to treat the mentally ill harsher than ordinary people (i.e., more likely to use coercive actions such as arrest). This policing pattern actually criminalizes these people who were supposed to be served by mental health programs. In contrast, Bittner proposed a “psychiatric first aid” policing hypothesis (Bittner, 1967), which states that police officers were usually lenient toward persons in psychiatric crises, less likely to arrest them and/or use force, and often resolved the incident in an unofficial way. According to this hypothesis, although police officers lacked professional knowledge of mental illness, they were willing to help mentally disrupted subjects get out of crises and divert them from the criminal justice system. Research around this issue has mainly focused on the coercive actions taken by police toward mentally disrupted persons they encountered. Two measures of coercive actions, arrest and use of force in encounters with the mentally ill, are mostly used in field research. Both hypotheses have gained some support from empirical research.

The criminalization hypothesis gained early support from an abundance of studies which consistently revealed that persons with mental illness have higher arrest rates than the general public (Durbin, Pasewark, & Albers, 1977; Link et al., 1992; Steadman et al., 1978). The most cited study supporting this theory is Teplin (1984). Using a sample of 1,382 police-citizen encounter events in Chicago, Teplin (1984) compared the arrest rates between people with and without mental illness. In her study, trained observers followed patrol officers and judged the mental status of suspects they encountered. She found that the rates of arrest for persons with mental illness were significantly higher than those of

the non-mentally ill who came into contact with police (46.7% vs. 27.9%). Hence, Teplin (1984) drew the conclusion that police officers intend to treat persons with mental illness as criminals.

However, some researchers (Engel & Silver, 2001; Novak & Engel, 2005) argued that early studies without multivariate analyses failed to control for the effects of suspects' demographic characteristics, severity of violent behaviors and demeanors, or other related factors pertinent to the coercive actions taken by police, thus possibly yielding misleading conclusions. Using two sets of data collected in 1977 and 2000, respectively, Engel and Silver (2001) reported that those citizens who police perceived as mentally ill in encounters were more likely to be involved with more serious offenses, to resist officers' orders, and to be influenced by drugs and/or alcohol. After controlling for these legal causes for arrest, situational factors, and some demographic variables, they found that being perceived as mentally ill by officers actually was associated with a reduced incidence of arrest. The researchers concluded, therefore, that mental illness serves as a protective factor for avoiding arrest. Similarly, using data from 617 police-citizen contacts in Cincinnati, Ohio from 1997 to 1998, Novak and Engel (2005) reported that the arrest rate for mentally ill suspects was lower than the arrest rate for ordinary suspects (20.4% vs. 28.0%), despite the fact that mentally disturbed suspects were more disrespectful and resistant toward police officers than normal offenders. These two studies strongly challenged the criminalization hypothesis.

Also, a few studies on use of force stand in line with these two studies.¹ Kaminski and colleagues (2004) examined police officers' self-reported use of force in 2,060 arrest

¹ Although there are an abundance of research suggesting that police are more likely to use force toward persons with impaired judgment than people who without impairment, most of them used combined

records from a southeast municipal police department. They reported that officers were 37% more likely to use minor force toward judgmentally impaired persons (drugs, alcohol, and/or mental illness), and 57% more likely to use serious force on impaired persons than on unimpaired suspects, even after taking hostility, possessing weapons, and demographic characteristics into account. However, when they disaggregated judgmental impairment into intoxication by drug, alcohol, and mental disorders, they did not find a correlation between mental illness and use of force. Johnson (2011) found that mentally unstable suspects were more likely to receive a higher level of force than mentally stable suspects (17.2% vs. 5%). However, mentally disturbed suspects were more likely to be violent, uncooperative, and to carry a weapon, than general suspects. After controlling for these factors, the association between mental illness and police use of physical force disappeared (See also Mulvey & White, 2013). Their findings indicated that more serious legal factors, a disrespectful manner, resistive behavior, and/or bizarre behavior rather than the suspect's mental status, per se, led to a disproportionately high arrest rate or use of force for persons with mental illness. After these factors were taken into account, it was found that police officers were not differentiating or allowing more lenience in response to mentally disrupted suspects than general suspects.

Notably, several recent studies employing multivariate analysis still reported contradictory results. Analyzing a sample of 747 self-reported use of force incidents in Philadelphia in 2002, Lawton (2007) reported that suspects who were perceived as “mentally unsound” were more likely to receive a higher level of force from police even after controlling for suspects' use of weapons, disrespectful manner, and intoxication.

measure of impairment which includes drug use, alcohol abuse, and mental illness. Only a few of them examined the specific relationship between use of force and mental illness (Johnson, 2011; Kaminksi et al., 2004; Kesic et al., 2013; Mulvey & White, 2013).

Using police use of force register data which includes 4,267 subjects in Victoria, Australia, Kesic et al. (2013) found that the police were more likely to use or threaten to use weapon-based force on suspects who appeared to be mentally disordered, even after taking into account the suspects' level of abusive language, substance use, and violent behavior. Although nearly half of suspects deemed mentally ill were injured during those encounters, they were no more likely to be injured than non-mentally ill suspects. Also, a suspect being perceived as mentally ill was not associated with an increased risk of officer injury. Most of the injuries in both groups were minor or there were no visible signs of injury.

Some researchers have suggested that the way police treat the mentally ill might not be simply classified as discriminatory, harsh, neutral, or lenient. The responses of police to the mentally ill are often mixed and may be affected by the interaction of the suspect's mental state and certain legal or situational factors. Mulvey and White (2013) surveyed 942 arrestees in a dozen law enforcement agencies in Maricopa County, Arizona in 2010 to identify the relationship between their mental status and the level of force used. They reported that although they found a null relationship between mental illness and general coercive force by police after controlling for pertinent situational and legal factors, they did find that persons with mental illness were more likely to receive highly serious force than were normal people. This finding implies that the dynamics of mental crises incidents involving confrontations might be different in comparison to ordinary police-citizen encounters. Furthermore, the way police respond to persons with mental illness may depend on the interaction of a suspect's mental status and certain legal or situational factors. In other words, the reactions of police to the mentally ill are not

consistent at different levels of the mentally ill's violent, disruptive, or disrespectful behaviors during the encounters. When these behaviors are at a low level, police tend to use non-violent tactics. But when the seriousness of the crime, the level of resistance, and the confrontational severity of mentally disturbed suspects exceeds a threshold that constitutes an imminent threat to officers or other citizens, officers are more likely to resort to the use of more serious force in order to get the situation under control in a quick and reassuring way.

3.2 CRISIS INTERVENTION PROGRAMS IN MENTALLY ILL INVOLVED ENCOUNTERS

To efficiently deal with law enforcement officers' encounters with mentally ill subjects, many jurisdictions adopt specific crisis response programs. The initial goals of such programs are to reduce arrest rates in the mentally ill population, reduce use of force and the risk of injury and fatality in police-citizen contacts involving the mentally ill, and divert minor offenders to appropriate health care. Among a variety of these programs, the most popular model is the Crisis Intervention Team (CIT), which was developed in Memphis, Tennessee (National Alliance of Mental Illness [NAMI], 2012; Reuland, 2004). There are several core elements of CIT. First, officers participate in the team on a volunteer basis. Second, participating officers receive forty hours of training, which focuses on identification of mental illness and specialized de-escalation techniques for persons in mental crisis. In addition, CIT officers take charge of the situation once they are called on to the scene. The final element is that a close partnership between police and local mental health care services and other stakeholders (i.e., no reject referral policy) must be established (Borum et al., 1998; Dupont, Cochran, & Pillsbury, 2007).

CIT was designed to lower response time, reduce arrest rates, provide appropriate care toward persons in mental crisis, and improve the safety of police and citizens involved in the encounters (Dupont et al, 2007). This program has received modest empirical support. Some researchers (Compton et al., 2014; Watson et al., 2010) have reported that CIT officers were more likely to refer mentally ill citizens they encountered to mental health services than non-CIT officers. This program also increased the confidence of police officers to handle cases involving the mentally ill (Borum et al., 1998, Davidson, 2014). Teller et al. (2006) found that CIT training was positively related with identification of calls involving possibly mentally ill individuals. A lower injury rate for both police and suspects with mental illnesses was also reported by Dupont and Cochran (2000) and Acker (2010). However, Watson et al. (2010) did not find that CIT had an effect on reducing arrest for mentally ill offenders. Also, a recent meta-analysis of CIT programs based on eight eligible studies reported a non-significant effect of CITs on arrest rates in persons with mental illnesses (Taheri, 2014).

Regarding the relationship between use of force and the CIT program, there were some mixed findings. Skeem and Bibeau (2008) reported that average violence potentials for CIT events were just minor to moderate, and police use of force was associated with a high violence risk rating. However, officers used force rarely, even in events with serious violence potential. Morabito et al. (2012) surveyed self-reported use of force in recent encounters involving a mentally ill person among 216 CIT trained officers and non-CIT trained officers from four districts of the Chicago Police Department. They reported a marginal positive association ($p < 0.1$) between CIT training and use of force. However, they found a significant interactive effect on the use of force between CIT training and

resistant demeanor, which means that officers responded differently for an increasingly resistant demeanor of suspects depending on whether they were CIT trained or not. That is, the use of force by CIT trained officers is the same as non-CIT officers when faced with low-level confrontation, but under high resistant demeanor circumstances, CIT trained officers are less likely to use force as compared to non-CIT-trained colleagues. This result is in line with the Skeem and Bibeau (2008) study. Also, compared with the finding that officers were more likely to be more coercive to mentally ill suspects in high intensity level encounters in Mulvey and White's study (2013), this finding suggests that CIT is specifically effective in reducing the use of force in such situations. However, Taheri (2014) found a null relationship between CITs and the use of force in her meta-analysis.

3.3 OFFICER SAFETY AND THE MENTALLY ILL

Although there were mixed findings regarding the way police treat the mentally ill they encounter and the effects of crisis intervention programs, the majority of the empirical studies consistently revealed that persons with mental disorders who came into contact with police were more likely to be resistant and to show violent behaviors than the general population (Engel & Silver, 2001; Johnson, 2011; Kesic et al., 2013, Mulvey & White, 2013; Novak & Engel, 2005). Furthermore, this population may have difficulty in understanding officers' intentions and may respond in an unpredictable manner. Tension may escalate rapidly due to such misunderstandings or result in inappropriate reactions during encounters. These situations may lead to the use of force if officers believe the suspects with mental illness are noncompliant or dangerous (Johnson, 2011). In any case, the probability that force will be used by police increases when they

encounter persons with mental illness acting out in the community (Johnson, 2011; Kesic et al., 2013, Mulvey & White, 2013). Accordingly, the risk of injury or death for police officers is assumed to be heightened in these situations. In this context, a reasonable concern about the safety risks posed to both the mentally ill and police during such encounters is raised due to their heightened likelihood of violent confrontation. Some descriptive studies have shown that police officers have higher injury and death rates when assaulted by mentally ill individuals compared to assaults by individuals without mental problems (Margarita, 1980; Treatment Advocacy Center, 2005). According to the Treatment Advocacy Center (2005), the likelihood of being killed by a person with mental illnesses for law enforcement officers was 5.5 times that of being killed by a member of the general public, and the risk of a law enforcement officer being murdered by a mentally ill person was even higher than that posed by a person with prior arrests for assaulting the police or resisting arrest (13% vs. 11%) (see also Brown and Patrick, 2001). Research about officers' perceptions of the dangerousness of encounters with the mentally ill showed that police considered these encounters to be one of the most dangerous situations (Treatment Advocacy Center, 2005).

Surprisingly, despite the aforementioned descriptive reports and studies of police use of force, there are few empirical studies focusing on the safety risk of law enforcement officers in encounters involving subjects with mental illness. Morabito and Socia (2015) analyzed about 6,000 use-of-force reports compiled by police in Portland, Oregon, from the year 2008 to 2011, and reported that the encounters with the mentally ill per se did not increase the likelihood of injury for law enforcement officers. Using an Australian sample, Kesic et al. (2013) found that most of the injuries in police-citizen encounters

involving mentally ill persons were minor or non-visible injuries. They also reported that encountering a suspect perceived as mentally ill did not significantly increase an officer's injury probability.

These findings are contradictory to the descriptive reports and studies about officers' perceptions of the dangerousness of mentally ill subjects. They implied that an elevated safety risk for officers created by encountering persons with mental illness may be only a perceived threat and not an actual one. However, some attention should be paid to the methodological limitations of these incident-level studies before we confidently adopt these conclusions. First, police encounters involving the mentally ill could be considerably under-reported. Existing research suggests that in certain situations, officers tend to solve cases in an unofficial way with a report never created (Bittner, 1967, Engel & Silver, 2001; Novak & Engel, 2005; Teplin, 1984). Therefore, many of these cases would not appear in officers' reports. Some other cases, despite strong doubts about the mental status of offenders, were not counted as encounters involving the mentally ill due to incomplete information (e.g., the recent case in which two NYPD officers were ambushed in their patrol car by a young man with history of mental illness, Goodman & Baker, 2014).

Second, even in circumstances where there are explicit definitions about encounters involving persons with mental illness, police officers often find it difficult to identify subjects with mental illness during police-citizen contacts. The ability of officers to distinguish the mentally ill from individuals under the influence, or persons acting out simply due to a bad mood, during very short encounters is quite questionable (Adkins, Burkhardt, & Lanfear, 2015; Alpert, 2015). This may be the reason some studies just

used a combined measure (i.e., judgmentally impaired persons) to include the mentally ill and persons under the influence of alcohol or drugs as a whole rather than separately identifying them (Alpert, Dunham, & MacDonald, 2004; Kaminski et al., 2004).

Moreover, there could be highly varied measurement errors regarding officers' dispositions and related contextual factors in police-citizen contacts². In studies using officers' self-reported data, informal dispositions, such as dumping persons with mental illness in other jurisdictions or mild physical contact occurring without any injury, although very coercive in nature, could be substantially underreported (Johnson, 2011). The information regarding related situational factors during confrontations could also be distorted, depending on whether it was gathered from officer-reported data or arrestee-reported data (Rojek, Alpert, & Smith, 2012). Employing observers to document police-citizen encounters could provide more detailed and accurate information, but because officers are aware of being observed, they may alter their routine practices and demonstrate more socially desirable behaviors when encountering mentally ill persons (reactivity bias, Mastrofski et al., 1998; Spano, 2005). All of these measurement issues could result in the misclassification of a wide range of important variables and lead to contradictory conclusions.

Finally, the generalizability of these studies is limited. There are considerable variations among jurisdictions in terms of local policing protocol, firearm regulation, available training, and the extent of collaboration between police and mental health services. Additionally, policing ideals and practices keep changing. Some specific

² A few studies used trained observers who ride along with officers to document the details of police-citizen contacts (Teplin, 1984; Engel & Silver, 2001; Novak & Engel, 2005). Some used officer self-reported data to track suspect's mental status, disposition, and situational factors (Kaminski et al., 2004; Johnson, 2011; Kesic, 2013; Lawton, 2007). One study used arrestee's self-identification as criteria of mental status and self-reported data to capture contextual variables (Mulvey & White, 2013).

programs, such as Crisis Intervention Teams (CITs), jail diversion programs, and mental health courts were developed to respond to increasing police encounters with mentally ill people. However, such developments are not consistent across all the jurisdictions. The great diversity of available options and resources police could use to deal with persons with mental illnesses they encounter may have a vast impact on risk assessment for police officers.

Since incident-level studies suffer the most from these methodological problems, a possible alternative approach could be ecological studies, which focus on the relationship between risk for the police and the mentally ill at aggregated levels. There are several advantages of an ecological study over an incident-level study in police safety research. First, an ecological study could address some of the measurement issues mentioned above. This type of study focuses on the effects of aggregate, environment, or global variables, for example, social structural factors, on the outcome of interest. Selecting reliable and routinely used aggregate-level variables can avoid some measurement obstacles in an incident-level study. Second, an ecological study could provide higher generalizability by analyzing data collected from multiple areas. The findings will give us a more general picture when their samples come from a larger population. Third, an ecological study could also be suitable to analyze rare event outcomes, which are injury and/or death in police safety research. It would be much easier to obtain enough outcome observations by aggregating data at a higher level research unit. Also, an additional longitudinal design could help identify the effect of temporally changing variables. It is especially useful to examine risks for police in the context of deinstitutionalization, in which the responses of law enforcement agencies and communities keep evolving. A

detailed discussion about the benefits and costs of longitudinal design is given in the next chapter.

To the best of our knowledge, the only ecological study investigating the relationship between the mentally ill and police safety is a preliminary study conducted by Kaminski (2007). In this study, Kaminski (2007) examined a time-series state-level data during the period of 1972-1996. He found a significant positive association between the rates of releasing mentally-ill patients and the numbers of the police slain, while controlling for socio-structural variables, such as violent crime rates, the percentages of minority residents, poverty rates, and the percentage of the population living in urban areas.

However, there still are problems that the researcher should consider in an ecological study. Among them, the most difficult one is the measurement of the risk for police. This problem plagues all police safety studies. Some studies have used officer perceptions regarding the mental status of suspects and the degree of threat (Ruiz & Miller, 2004; Watson, Corrigan, & Ottati, 2004). But this variable is more about measuring subjective perceptions rather than actual risk. Though instructive for reflecting an officer's stress level based on expectations, such a measure could yield misleading findings and inflict unnecessary discrimination on persons with mental illness (Morabito & Socia, 2015).

Some other studies have used injury as the indicator of risk for police. Even though definitions of injury seem simple, straightforward, and instinctively understandable, some problems can arise in practice. There might be specific instructions for officers on how to report injures, but the line between an injury and a non-injury sometimes can be very blurred. It is expected that there is significant variation in the reporting protocols among different law enforcement agencies. Hence the reporting of injury incidents is subject to

substantial reporting and recording biases (Alpert, 2015). However, there is national-level data on nonfatal assaults on police available from the Federal Bureau of Investigation's (FBI) Law Enforcement Officers Killed and Assaulted (LEOKA) program. The data include the number of officers injured in assaults by force type (e.g., physical force, firearm, edged weapon). This data seems like an ideal source to measure the risks for officers during encounters with the public. Unfortunately, the nonfatal assault data is only collected from those agencies that participate voluntarily, rather than all the law enforcement agencies in the United States. For example, the data for the year 2008 only covered 10,110 law enforcement agencies (LEOKA, 2009), while there were an estimated total of 17,985 law enforcement agencies across the country (Reaves, 2011). Moreover, the seriousness of these assaulting incidents has a wide variation. The assault data also includes the non-injury cases in which offenders could have caused the injury of officers. In practice, one incident could be counted as a non-fatal assault when a firearm was only present at scene, even though the nature of the incident was not violent at all (Kaminski, personal communication). These facts, plus the measurement biases mentioned above, make it impossible to accurately estimate the safety risk for police from the nonfatal assaults data.

Fatal assault on police is an alternative measure much less prone to error and has been used in a number of empirical studies (e.g., Batton & Wilson, 2006; Jacobs & Carmichael, 2002; Kaminski & Marvell, 2002; Kaminski, 2008; Kent, 2010). This proxy indicator of serious violence against the police is the measure with the highest reliability. The data on the felonious killing of officers is systematically recorded by the FBI with decent accuracy. Unlike injuries, which are subject to individual officer's discretion or the local

agency's reporting policies, the death of officers is easy to define. For the purpose of capturing police killers, local law enforcement agencies notify and submit related information to all other agencies, including the FBI (Chapman, 1998:8). In addition, since murders of police are usually the top news in local media, FBI field offices also record and submit notification to FBI headquarters in Washington, DC. The FBI can also be informed by several organizations, e.g., the Concerns of Police Survivors (COPS) and the National Law Enforcement Officers Memorial Fund (NLEOMF) (LEOKA, 2014). After being notified, the FBI contacts the local law enforcement agencies and requests additional information regarding the fatal incidents (LEOKA, 2014). Therefore, the LEOKA fatality data suffers from the least measurement error.

However, the weakness of this indicator should be mentioned as well: felonious killings of officers only represent a fraction of all the safety threats to police officers. Research suggests that many nonfatal attacks are indistinguishable from fatal attacks in motive, intent, and dangerousness (Zimring, 1968; 1972). Looking only at murders of officers in the line of duty could underestimate the safety risk for the police.

Another problem with an ecological study is spatial and temporal autocorrelations in the data. As discussed above, either injuries or death of police officers during police-public encounters are rare events (e.g., the average number of murdered officers was 51 per year in the United States in the last decade, see LEOKA, 2005-2014). The rarity of observations makes analysis beyond descriptive statistics difficult, even using aggregated level data. A common solution to this situation is combining the rare event incidents across space and over time to yield enough observations. This also introduces substantial spatial and temporal autocorrelation issues into the analysis.

When analyzing the distribution of some phenomena across geographically defined areas or a series of time periods, the issue of spatial or temporal dependences (autocorrelations) should be considered (Knorr-Held, 2000). Such dependences refer to the tendencies of observing similar scores in adjacent areas or sequential time periods due to the similar characteristics (often unmeasurable) in these regions or time frames. Spatial or temporal dependence violates one of the basic assumptions of regression techniques, i.e., independence among observations/errors, thus causing statistical problems in regression analysis. Therefore, regression models that account for such autocorrelations are needed to provide a clear map of incident risk, improve the estimation of covariate parameters, and reveal residual spatial or temporal patterns induced by unmeasured variables (Lawson et al., 2000; Wall, 2004). Traditional frequentist analytic methods, however, have limited ability to handle the dependence in space and time simultaneously (Law, Quick, & Chan, 2014). Luckily, the recent advance of statistical techniques has made it possible to solve this problem in a relatively simple way. Chapter 5 gives a more detailed discussion on this topic.

In summary, the relationship between the victimization risk for police and increased police-citizen encounters involving mentally ill persons after deinstitutionalization is substantially understudied. Many methodological obstacles impede the research in this area. However, an ecological design is practical to avoid these obstacles plaguing incident-level police safety risk studies. Additional longitudinal feature of the data can be used to assess the effect of temporally varying risk factors. Following this thought, the present study extends Kaminski's (2007) work to examine the impact of deinstitutionalization on police safety more thoroughly. Even though fatal assault on

police is not a perfect measure of risk for police, it still has the highest measurement validity and reliability. After comparing the pros and cons of the available measures of serious violence against the police, the present study will use the number of felonious killings of officers as the dependent variable. There are several major improvements in the present study. First, Bayesian hierarchical modelling is employed to incorporate geographical and temporal variations introduced by the aggregation of data. Second, more potential risk factors are considered in the analysis to reduce possible confounding effects. Moreover, a mapping strategy is used to visualize the geographical pattern of risk estimates, after controlling for related risk factors.

CHAPTER FOUR

THEORETICAL FRAMEWORK OF POLICE MURDERS

Since the felonious killing of law enforcement officers is chosen as the indicator of the occupational hazard risk for officers, it is worthy of a discussion on the theoretical framework of officer homicides. A review of examined risk factors in related empirical studies is followed. In doing so, we can have a better understanding of police homicides, identify the theoretical linkage of relevant risk factors, and evaluate the values of these factors in the present study.

4.1 EVOLUTION OF THE THEORETICAL FRAMEWORK

Earlier studies of officer homicides mainly focused on the effects of the negative environmental structural factors used in violent crime research without deep theoretical explorations (Bailey, 1982; Bailey & Peterson, 1987, 1994; Moody, Marvell, & Kaminski, 2002; Mustard, 2001). Much research generally made an assumption that violence against police is a byproduct of common violent crime, since more police murders took place when encounters between police and offenders increased along with the rising crime rate (Cardarelli, 1968; Creamer & Robin, 1970; Margarita, 1980). Under this assumption, officers' chances of getting murdered would be higher if more serious crime offenders were present in the community, some of whom possess the motivation to escape and/or resist law enforcement agents' detecting, tracing and arresting (Fridell, Faggiani, Taylor, Brito, & Kubu, 2009; Kaminski, 2002). Therefore, violence against the police in particular should share considerable common traits with ordinary violent crime. In this

view, those adverse context variables such as poverty, family disruption, ethnic heterogeneity, and population instability, should influence and could predict felonious killings of officers, just like the effects of these variables verified in traditional violent crimes studies (Kaminski & Marvell, 2002; Peterson & Bailey, 1988).

A political perspective, based on conflict theory and the racial threat hypothesis (Eitle, D'Alessio, & Stolzenberg, 2002; Jackson, 1989), argues that violence against police has reflected suppressed classes' inarticulate protest or primitive rebellion toward the state's control force, and thus can explain the overrepresented number of black offenders in police killing cases. According to this theory, minorities and/or members of the lower classes have very limited legitimate access to ask for their economic and political rights or to seek remedy for mistreatment, resulting in a strong sense of injustice. Therefore, attacking law enforce agents, the symbol of the State's powerful control over the lower class, becomes a form to express this resentment of injustice (Jacobs & Carmichael, 2002). However, the findings under this hypothesis have been mixed. Peterson and Bailey (1988) and Chamlin (1989), found no association between black-white income inequality and officers attacks. Jacob and Carmichael (2002) and Kent (2010) found that the presence of a black mayor, an indicator of blacks' high political status, has an inverse association with the murders of officer, whereas white-black income inequality has a positive correlation with police killings. However, after a reexamination of Jacob and Carmichael's (2002) data, Kaminski and Stucky (2009) reported that neither the presence of black mayor or racial income gap can predict police homicide.

Some later studies (Fridell, Faggiani, & Brito, 2004; Fridell et al., 2009; Kaminski, 2002, 2004, 2008) introduced criminal opportunity theory, which views crime activity as a function of occupational proximity, risk exposure, target attractiveness, and protective guardianship (Cohen & Felson, 1979; Hindelang, Gottfredson, & Garofalo, 1978; Miethe & McDowall, 1993), to elucidate the mechanism of serious violence against officers.

According to Cohen, Kluegel, and Land (1981:507), proximity is “the physical distance between areas where potential targets of crime reside and areas where relatively large populations of potential offenders are found.” The closer the distance between the target and the pool of potential offenders, the higher the victimization risks for the target. Cohen et al. (1981) also defined exposure as “variations in physical visibility and accessibility of potential targets (persons or objects) to potential offenders as determined by personal characteristics of the potential targets” (Ibid: 507, note 3). In opportunity theory, proximity differs from exposure in that proximity is a spatial concept which describes the geographical closeness between potential targets and offenders, while exposure is a context concept, which emphasizes the “physical visibility and accessibility” of targets to offenders determined by targets’ personal characteristics (Ibid:507, note 3). According to this distinction, in the research of police homicides, a criminogenic environment is classified as a proximity factor since police officers are close to the pool of potential offenders in such an environment. Alternatively, an aggressive policing policy is classified as an exposure factor because in such a context motivated offenders more easily become aware of the existence of police officers, which raises the chances of

police-offender confrontation.³ Attractiveness is referred as the symbolic or monetary value of targets to motivated offenders (Miethe, Hughes, & McDowall, 1991:166). In police killings research, it can be interpreted as the potential benefits offenders could gain if they kill the officers (Kaminski, 2002). It is reasonable to assume that the more serious crimes the offenders commit, the stronger motivation they have to murder the police officers who are trying to prevent the crimes or arrest the offenders. Guardianship is “the effectiveness of persons...or objects in preventing violations from occurring, either by their presence alone or by some sort of direct or indirect action” (Cohen et al.,1981: 508). For example, good training and equipment, conservative patrol patterns, and mandatory body armor wearing policies are conceived as guardian factors to lower an officer’s risk of being slain. Kaminski (2002, 2004) suggested that in police homicides studies, the concept of guardianship and attractiveness often overlap, since officers with better protection are hard to attack successfully and deemed as less attractive by motivated offenders.

From the perspective of opportunity theory, the crime byproduct assumption mentioned above could be partially correct, because adverse structural conditions contribute to create a crime promoting environment. This increases the spatial proximity to motivated offenders and attractiveness of officers as targets for attack during arrest attempts, and affects the rates of police victimization (Fridell et al., 2009; Kaminski, 2002). These negative structural factors, through either strain perspective or social

³ Unfortunately, the line between these conceptual components is not always clear and obvious. In actuality, many variables may represent multiple conceptual components of opportunity theory. For instance, high rates of serious crime known to officers represent both close spatial proximity to potential offenders and the attractiveness of attacking police to avoid apprehension and punishment.

control perspective, significantly enlarge the pool of active and potential criminals by producing a more criminogenic context. For police, whose task is to deter crime, a larger proportion of possible offenders in the community represents closer proximity to a dangerous work surrounding. Hence, the victimization risk for police officers is expected to be greater in these areas (Fridell et al., 2009; Kaminski, 2002).

Moreover, the impacts of adverse structure conditions are not limited to crime facilitated contexts per se; they comprise many other protective elements of police safety. For instance, besides creating a criminogenic environment, adverse structural factors also lead to intense interpersonal relationships, forcing officers to become involved with more daily interpersonal disturbances and domestic violence when they perform their routine duties (Ellis, Choi, & Blaus, 1993). Such cases increase officers' exposure to potential dangers when a situation becomes aggravated, which then increases their likelihood of being assaulted and killed. Furthermore, negative eco-social structures have an adverse impact on guardianship. These factors reduce assistance, resources, and respect given to officers from the communities they serve. This makes officers more vulnerable to police killers. According to opportunity theory, attacks aiming to kill police officers would occur, and succeed more easily under diminished guardianship.

From the discussion above, one can see that opportunity theory is a useful theoretical framework to understand and study police murders. It can be easily used to connect and organize a wide variety of regressors by considering them as indicators of the components of proximity, exposure, attractiveness, and guardianship. It also provides an efficient way to include new candidate risk factors into the examination. As mentioned above, some mentally ill individuals released into communities during

deinstitutionalization may have heightened violent tendencies due to inadequate treatment in the community. These persons enlarge the pool of potential offenders, thus increasing the proximity of police to potential attacks. Therefore, the impact of deinstitutionalization should be considered in assessing the murder risk for officers.

4.2 RISK FACTORS EXAMINED IN PRIOR RESEARCH

Criminogenic environment

Factors related to the criminogenic environment include those most used social structural factors, such as residential instability, racial heterogeneity, economic deprivation, family disruption, population density, age structure, and local crime level.

From the point of view of social disorganization theory, factors affecting social relations and informal controls can influence police homicide risk since these factors are associated with high levels of crime and deviance, which put officers in close proximity to a high-risk working environment (Kaminski, 2002). Residential instability, racial heterogeneity, economic deprivation, family disintegration, and large and dense populations fall into this category.

Residential instability, racial heterogeneity, and economic deprivation are three main indicators of social disorganization initially identified by Shaw and McKay (1969). These factors were found to be strongly associated with weak informal social control over deviant conduct in local communities. Communities with high residential mobility, racial heterogeneity, and economic deprivation usually lack well-functioning conventional institutions (i.e., stable families, churches, volunteer organizations) to monitor and regulate delinquent behaviors. The recently developed social capital/collective efficacy framework further elaborates that the aforementioned adverse social-economic factors

impede communication between community members, make it difficult to form stable social relations, and damage a community's ability to nurture mutual trust and support, thus resulting in a reduction in a community's willingness and capability to control disorderly behaviors (Parker, McCall, & Land, 1999; Sampson & Groves, 1989; Sampson & Laub, 1993; 2005). Therefore, residential instability, racial heterogeneity, and economic deprivation elevate the potential for delinquency, which in turn increases the proximity of police to potential offenders.

Residential mobility is usually measured by the percentage of the population that resides in the same residence for five years. Residential instability is a conventional social structural variable examined in criminal literature, and is found to be correlated with civilian homicides and other crimes (Land, McCall, & Cohen, 1990; Parker, McCall & Land, 1999; Sampson & Wilson, 1995). However, few studies have examined its impact on police homicides. Kaminski (2002) reported a positive association in the bivariate analysis, which contrasts with the expected direction.

Most prior studies used the percentage of black, Hispanic, or non-whites as a measure of racial/ethnic heterogeneity⁴ and reported mixed findings as related to general crime (Land, McCall, & Cohen, 1990; Parker, McCall, & Land, 1999). Some studies (Bailey & Peterson, 1994; Fridell & Pate, 1995; Peterson & Bailey, 1988) found that the percentage of African-Americans in a population had no impact on the homicide rates of police, while others (Bailey & Peterson, 1987; Chamlin, 1989; Jacobs & Carmichael, 2002; Kaminski, 2008; Kaminski & Stucky, 2009; Kent, 2010) reported that

⁴ Another indicator, racial segregation, which is defined as the extent to which two or more racial groups are unequally distributed among certain regions, could be considered to represent racial heterogeneity (Massey & Denton, 1988). In practice, however, this indicator shows inconsistent relationships with civilian homicides studies (Land, McCall, & Cohen, 1990; Parker, 2001; Parker, McCall, & Land, 1999), and is seldom used in the research on homicides of police officers (except Kaminski, 2002; Kent, 2010).

greater percentages of black citizens in a population predicted higher victimization risks for officers. However, Bailey and Peterson (1994) reported an inverse association between police homicides and the percentage of black individuals in a population.

It should be noted that a political explanation of the positive association between percent black and police homicides also exists. This explanation is based on conflict theory and the racial threat hypothesis (Blalock, 1967; Eitle, D'Alessio, & Stolzenberg, 2002; Jackson, 1989), which argues that racialized struggle between whites and other minorities drives white elites to use state sanctioned force to direct rigorous, discriminative social control over minorities in the fear of losing their own economic and political powers. This political explanation posits that violence against police has reflected a form of suppressed minority groups' unarticulated protest or primitive rebellion toward the state's control forces, and thus can explain the relationship between percent black and the killings of police.

According to this theory, minorities have very limited legitimate access to ask for their economic and political rights or to seek remedy for mistreatment, resulting in a strong sense of injustice. Therefore, attacking law enforcement agents, the symbol of the State's powerful control over the lower class, becomes a form to express this resentment of injustice (Jacobs & Carmichael, 2002). The findings under this hypothesis have been mixed. Peterson and Bailey (1988) and Chamlin (1989), found no association between black-white income inequality and officer attacks. Jacob and Carmichael (2002) and Kent (2010) found that the presence of a black mayor, an indicator of blacks' increased political status, has an inverse association with the murders of officers, whereas white-black income inequality has a positive correlation with police killings. However,

after a reexamination of Jacob and Carmichael's (2002) data, Kaminski and Stucky (2009) reported that neither the presence of black mayor or racial income gap can predict police homicide.

Although this political explanation for police homicides warrants further examination, the racial threat perspective used in this explanation is especially relevant when considering the change in the characteristics of those released from mental institutions during deinstitutionalization, and the effect of this change on police homicides. Recall that during the radical phase of deinstitutionalization, more racial minorities and young male patients were released. Some existing research attributes this change mainly to budget saving motivations (Mechanic & Rochefort, 1990). However, it is possible that more minority patients, especially those young male patients, could have been institutionalized in the early periods because they were perceived as more violent and dangerous than white patients due to the symbolic threat (Blalock, 1967). For the same reason, they could be more likely to have delayed releases relative to white patients. Therefore, their portion of the mix of those released increased during the radical phase. However, those released minority patients are still considered as crime-prone individuals by mainstream society, thus facing greater discrimination than other released patients. This situation, plus the existing racial inequality in economic and political status, could lead to those patients' strong anger toward society, which might result in increased violence against police.

Poverty, low income, and unemployment have often been adopted as indicators of economic deprivation and expected to be associated with high crime levels, according to social disorganization or strain theory (Sampson, Morenoff, & Earls, 1999; Sampson &

Raudenbush, 1999), thus raising the chances of police slayings. Prior research provided modest support to the effect of poverty. Bailey (1982), Bailey and Peterson (1987), Peterson and Bailey (1988), and Chamlin (1989) reported significant and positive associations between poverty and police murders in 2 of 11, 6 of 12, 2 of 8, and 2 of 3 regression models, respectively. There was also some weak evidence for the effect of median household income. Kaminski and Marvell (2002) found a negative association between income and killings of police officers in their national longitudinal analysis. Kent (2010) reported negative significant coefficients of median household income in 2 of 3 models. The findings of the role of unemployment were mixed. Bailey (1982), Batton and Wilson (2006), and Kent (2010) found positive associations between unemployment and the fatal victimization of officers, but other studies (Kaminski & Marvell, 2002; Lott, 2000; Peterson & Bailey, 1994) did not report significant relations.

Studies using social structural factors as regressors found that these three variables (poverty, median household income, and unemployment) were usually strongly correlated with each other, and can be grouped into one main component from principal component analysis (Fridell et al., 2009; Land et al., 1990, Kaminski, 2002, Kaminski & Stucky, 2009; Kaminski, 2008). This component has varied names in different studies, but essentially is viewed as an indicator of economic deprivation or disadvantage. The findings of the effect of this component on the serious victimization of officers are not consistent across studies. Kaminski and Stucky (2009) and Fridell et al, (2009) reported non-significant effects at city and agency-levels respectively. However, Kaminski (2002) identified positive effects of economic deprivation in most of his models at agency-level.

Also, a significant effect of economic deprivation on the homicides of police at county-level was reported by Kaminski (2008).

Besides absolute economic deprivation, relative economic deprivation also contributes to create criminogenic environments. Since people perceive that their legitimate means to gain necessary income or other reasonable needs are limited, they are more likely to feel injustice and frustration and respond in an aggressive and illegal manner (Blau & Blau, 1982). Several indicators of relative economic strains, such as GINI index or income inequality, have been explored in police homicide research, but with inconsistent findings. Peterson and Bailey (1988) found a null effect of income inequality and racial income inequality in their models. However, Chamlin (1989) reported a significant negative effect of GINI index in 1 of 3 models estimated, while Kent (2010) found that the ratio of Black-to-White incomes were positively related with the murders of police.

Adverse family structure factors, such as divorce and single parent families, can substantially impact informal social controls. Divorce rate is the most used measure of family disruption in the research on police murders. Although not significant in all models, many studies have provided some evidence of a positive relationship between divorce rates and police killings (Bailey & Peterson, 1994; Chamlin, 1989; Peterson & Bailey, 1988; Jacobs & Carmichael, 2002; Kaminski & Marvell, 2002) at different levels of aggregation. However, the percent of single-parent households was examined by Jacobs and Carmichael (2002) with a null predictive value.

An increase in population density is believed to heighten the levels of deviance, since it weakens social control mechanisms through superficial interpersonal connections,

increasing anonymity, and diminishing social participation in local affairs (Brantingham & Brantingham, 1984:151-155; Land, McCall, and Cohen, 1990:927; Sampson, 1986:5). An officer's chance of encountering criminal events is expected to rise due to the dense population, which in turn elevates the officer's risk of being killed. The association between population density and murders of police has been examined by several studies. Fridell and Pate (1995) reported that population density was negatively related to the killings of officers in their model for the 1985-1992 period, but found a null relationship in their model for the 1977-1984 period. In Kaminski's study (2002), population density was significant in only one of three cross-sectional models, but a significant interaction between arrest and population density was found in three waves of cross-sectional analysis and in the panel analysis. This result indicated that the effect of arrests on police homicides was modified by population density. Although arrests were generally positively associated with higher risks of homicide for police officers, such a relationship diminished in areas with high population density. This is probably because high population density makes it more likely that third parties are present, which could either deter the offender's attack, or offer the officer prompt assistance to avoid fatal victimization (Kaminski, 2002).

It is generally accepted that the level of violence is positively related to the proportion of teenagers and young adults in an area (Hirschi & Gottfredson, 1983; Messner & Rosenfeld, 1999:36). Therefore, the effect of age structure was considered in several police fatal victimization studies, as it could impact the proximity of officers to motivated offenders. However, most of the studies reported non-significant effects for the age structure variable (Bailey & Peterson, 1994; Fridell & Pate, 1995; Kaminski &

Marvell, 2002). Only one study (Bailey & Peterson, 1987) reported a significant relationship. Age structure variables were included in Lott (2000) and Mustard (2001) studies, but their effects were not reported.

Another set of indicators of criminogenic conditions are the offenses known to the police, which directly represent the levels of crime in an area. These factors are also assumed to be correlated to the proximity of officers to motivated offenders, thus being expected to have impacts on felonious killings of officers, but empirical studies show mixed findings. Null effects of violent crime, property crime, and index crime were reported by Bailey and Peterson (1987) and Peterson and Bailey (1988). Chamlin (1989) found a negative association between index crimes and killings of officers in three of six models. Some other studies (Fridell & Pate, 1995; Jacobs & Carmichael, 2002; Kaminski, 2003), however, found significant positive effects of violent crime rates on murders and aggravated assaults of police officers. Officers' murder rate was found to be positively significant by Jacobs & Carmichael (2002) and Baton and Wilson (2006). Besides finding a positive effect of arrests for serious crime on police homicides, Kaminski (2002) also reported an interaction effect of arrest and population density. Although the war on drugs substantially increases the chances of contacts between officers and potential offenders, the effect of drug-related crimes has not been much examined. One study (Kaminski & Marvell, 2002) used a linear increasing and decreasing trend variable to represent the effect of the crack years in different time periods, but provided a null finding.

It is worthwhile to mention that strain theory has also been used to explain the effects of the aforementioned socio-economic characteristics on local crime levels (Merton, 1938; Agnew, 1992), which in turn relates to the risks of police homicides. As Merton (1938)

described, individuals living in areas with adverse structural factors have few legitimate channels to achieve socially accepted goals (i.e., monetary success), and may experience strains which could lead to hostility and frustration toward their society. Therefore, some of them may respond by committing crimes to achieve those goals. By proposing a general strain theory, Agnew (1992) substantially broadened the range of the sources of strains. According to Agnew (1992), in addition to the economic strain emphasized in classic strain theory, many other negative relationships may cause strains and could trigger anger and frustration, thus increasing criminal activities. This theory connects all the criminogenic factors mentioned above with heightened crime rates, because economic disadvantage, disrupted family structure, racial discrimination/segregation, transient and crowded housing conditions, and victimization of violent crime are all stressful conditions which may cause strains and lead to negative emotions. Such strains and negative emotions increase the likelihood of committing deviant acts.

This perspective has a unique utility to examine the potential elevated violence against police in the mentally ill population. Compared to the general population, people with mental illnesses are more vulnerable to those undesirable socio-economic circumstances. The strains caused by those adverse structural factors may trigger the relapse or exacerbation of those people's mental illnesses, which can drive them to exhibit excess violence behaviors (Silver & Teasdale, 2005). Some mentally ill persons may resort to drugs or alcohol to cope with these stresses, which further increases their violent tendencies (Steadman et al., 1998; Volavka & Swanson, 2010). Moreover, the stigma of mental illness could introduce additional strains to persons with mental illnesses, such as the feeling of being unjustly treated or the heightened risk of being a

crime victim (Teplin et al., 2005), which is the result of discrimination, rejection, and avoidance by other people. All these strains may increase violent behaviors of mentally ill persons, and could have an impact on the safety risk for police.

Other factors

In addition to adverse structural conditions, many other factors could affect violence against officers from the view of criminal opportunity theory. For instance, agency organizational policy and policing practices, such as mandatory wearing of body armor, conservative foot patrol policies, sufficient emergency training, up-to-date side firearms, and high level first-aid availability could all enhance guardianship, while aggressive arrests and high officer density could increase exposure and proximity (Fridell et al., 2004; Fridell et al., 2009; Kaminski, 2002).

The data on most of these factors can only be collected at the agency-level. However, there are only two studies that focus on the effects of agency practice and policy on the serious violence against police. Kaminski (2002, 2004) found that most agency-level policing factors, such as the proportion of one-officer patrol units, the percentage of foot patrol assignments, mandatory vest-wearing requirements, semiautomatic sidearms (versus revolvers) and chemical agent equipment, educational level, academic training, and increased female officers employment, did not predict the felonious murders of officers. However, arrest was positively associated with homicide of police in all four cross-sectional models. Similarly, Fridell et al. (2009) did not find significant effects for officer training hours, the percentage of one-person units, dispatcher follow-up policies, or the levels of information updated to the dispatched officers. However, they reported that agencies supporting aggressive policing culture were more likely to experience

police homicides and serious victimizations. They also found that agency promotion of body armor use was positively associated with the number of felonious killings of police, which was the opposite of their expected direction. They explained this finding as a result of reverse causality in which the existing high victimization risk for police in specific agencies pushes the police administration in these agencies to implement more aggressive vest wearing policies.

Incarceration is assumed as an indicator of formal social control and examined in many civilian homicide studies. It could affect the number of police killings due to the effect of incapacitation or deterrence (Kaminski & Marvell, 2002).⁵ It is logical to believe that sentencing more offenders to prisons and jails could shrink the pool of potential police killers, decreasing the proximity of officer to motivated offenders, but the empirical findings are mixing. While Kaminski and Marvell (2002) and Batton and Wilson (2006) found a negative relation, Moody et al. (2002) reported a null effect of prison population on police homicides. Besides its linkage to police homicides, the incarceration rate is closely related to the change in the psychiatric institutionalized population (See the discussion in section 2.2).

Firearm availability is viewed as a factor influencing proximity, because the easier it is for people to possess guns, the larger the population of potential offenders who could use firearms to harm police officers. Hence, firearm accessibility, operationalized by a variety of measures, was examined by several studies, but with conflicting findings.

Fridell and Pate (1995) found that gun-related crime was positively associated with the

⁵ Execution is another formal control indicator which could influence police murders through similar pathways. However, the empirical evidence for the effect of execution is very weak. Among several studies testing the association between the death penalty and felonious killings of officers (Bailey, 1982; Bailey & Peterson, 1987; Bailey & Peterson, 1994; Kaminski & Marvell, 2002; Moody et al, 2002; Batton & Wilson, 2006), only Batton and Wilson (2006) report a positive effect.

number of police slain. However, Southwick (1998) reported that firearms per capita had no predictive value in the police homicides model. Kaminski and Marvell (2002) tested the effect of firearm use, measured by the proportion of homicides by firearms, but did not find a significant effect. Contrary to the general expectation, Mustard (2001) and Moody et al. (2002) found a negative association between shall issue law and police killings in 6 of 16, and 6 of 12 models, respectively.

Geographical features were examined in several studies. Some descriptive reports (LEOKA, 1972-2003) showed higher murder risks for both civilians and police officers in southern states, compared to other states. Some scholars attributed these heightened risks to the southerners' subculture, in which physically aggressive response gains more justification when one's honor and manliness are challenged (Wolfgang & Ferracuti, 1982:215). A few studies on killings of officers examined whether the number of police killings was influenced by a unit's regional location. Peterson and Bailey (1988), and Fridell and Pate (1995) reported null effects for the southern region indicator. However, Kaminski (2008) reported that the homicide risks for police were higher in the South, the Midwest, and the West than in the Northeast, and there was no significant difference in risks across the South, the Midwest, and the West. Bailey and Peterson (1987) found significant effects of the South in only two of twelve regression models. Therefore, the evidence of the effect of the South on the death of officers on duty is mixed.

4.3 LIMITATIONS OF PRIOR RESEARCH

A considerable number of social control variables, economic strain variables, and agency policy variables have been extensively examined in aggregate level research. Unfortunately, the findings of prior research reached few consistencies. Kaminski

(2008:351) commented that “more than two decades of research on police homicides has failed to identify virtually any regressor that is statistically significant and of the same sign across all models or studies.” The differences in the regression models, the nature of the units of analysis (national, states, counties, cities) and the nature of the data and design contribute to this problem. A brief discussion on these differences may reveal the limitations of prior research and suggest possible improvement in the present study.

(1) The choices of regression model. Early research mainly used the Ordinary Least Squares (OLS) regression to model the risk of police murder (Bailey, 1982; Bailey & Peterson, 1987; 1994; Chamlin, 1989; Fridell & Pate; 1995; Lott, 2000; Peterson & Bailey, 1988; Southwick, 1998). However, OLS regression is not appropriate for modelling the felonious murders of police officers, because the killings of officers are rare events, which do not follow a normal distribution. Later studies have widely applied Poisson or negative binomial models to estimate the fatal victimization of officers (Jacobs, & Carmichael, 2002; Kaminski, 2002, 2004; Kaminski, 2008; Kaminski & Stucky, 2009; Kent, 2010; Moody et al, 2002; Mustard, 2001). Poisson is good at modelling low count outcomes, and negative binomial is an alternative to Poisson if overdispersion is an issue, which is very common in practice. If a likelihood-ratio test on the overdispersion parameter is significant, negative binomial models should be used. Still, there is an issue, excess zero counts, that needs to be solved. Recall that police homicides are rare. Usually, most enumeration units report zero police killing incidents, yielding zero-dominant data. The presence of excess zeroes severely distorts the distribution of the data. In such cases, Poisson or negative binomial models could

produce inaccurate estimates. Unfortunately, most studies have not paid enough attention to this issue (Kaminski, 2002, 2004, 2008; Kaminski & Stucky, 2009).

(2) The unit of analysis. The influence of the choices of unit of analysis may be another reason for these studies' conflicting findings. In spatial analysis, researchers find that choosing different scales or shapes of aggregated spatial units could yield different statistical relationships between the outcome and predictors (Gehlke & Biehl, 1934; Openshaw & Taylor, 1979). This phenomenon is called the modifiable area unit problem (MAUP), which is closely related to the concept of the ecological fallacy (O'Sullivan & Unwin, 2010). Police murder studies have often aggregated police homicide incidents across space and over time to yield enough observations. Different levels of spatial unit are used. Smaller spatial units tend to have more homogeneity in some within-unit characteristics, such as social-economic structures, community resources, or agency policing cultures, than larger geographical units, thus appearing more appealing in police homicide research. However, due to the scarcity of the observations, the studies based on county or city-level data have to aggregate the outcomes over a very long time period (i.e., over a decade), or only sample areas with large populations (Jacobs, & Carmichael, 2002; Kaminski, 2002; 2008; Kent, 2010). A long temporal aggregation, which brings in tremendous temporal heterogeneity, hampers the ability to estimate effects of the covariates accurately. Restricting the research only to areas with high populations, which excludes incidents that happened in areas with small populations, raises concerns about the findings' generalizability. In comparison, state-level data, despite having more within-unit spatial variation, introduces much less within-unit temporal heterogeneity, as these data can produce acceptable counts of observations over a relatively short time

period. In fact, grouping state-level observations over an appropriate period of time can also reduce excess zeroes in the data.

(3) Data structures. In the studies adopting Poisson or negative binomial models, some (Jacobs, & Carmichael, 2002; Kaminski, 2008; Kent, 2010) have used cross-sectional data. A cross-sectional design is easy to implement and analyze, but it has very limited inference ability due to its static nature. It cannot detect the historical effects of factors since it does not allow temporal variabilities across research units (Kramer, 1983). This limitation severely confines cross-sectional research's usage. Time-series design brings in the variations in historical context, but for only one observation unit. Such a design could be used to identify temporal trends of the variable of interest and shed insight onto the temporal relationship between risk factors and the outcome. However, the lack of variations in spatial units in time-series analysis means that the generalizability of such an analysis is limited. Bailey and Peterson (1994), Southwick (1998), and Kaminski and Marvell (2002) all analyzed national time-series data, but they did not employ count models (i.e., Poisson), which are more appropriate for rare event data. A longitudinal study which repeatedly collects observations from multiple units at different time points can provide more information about the temporal effects of the independent variable. Depending on whether the number of units (N) exceeds the number of time periods (T), longitudinal data could be further classified as panel data (if $N > T$) and pooled time series cross-sectional (TSCS) data (if $N < T$) (Stimson, 1985). These longitudinal designs are more efficient to identify the effect of temporally varying variables than the cross-sectional or time series designs, thus providing a clearer picture of the relationship between the predictors and the outcome. However, the analysis of

longitudinal data of police homicide needs to consider the autocorrelations in time and/or space. Moody et al. (2002) estimated fixed-effect Poisson models of killings of officers, using state-level panel data from 1973-1998, but did not fully address spatial and temporal autocorrelation. Kaminski (2002, 2004) estimated a panel model in addition to cross-sectional models in four time periods, but the sample was restricted to 190 large municipal police departments.

There has been growing interest in examining the distribution and the factors that affect the variations of hazard outcomes involving both spatial and temporal information. A spatial-temporal mapping analysis can not only illustrate the trend patterns over time and spatial pattern across regions simultaneously, but also depict clear relationships between the response variable and related risk factors. It can accurately estimates the risks of outcome incidents after taking into account important risk factors and variation in space and time. Moreover, it can discern certain patterns from residuals due to unmeasured or unobservable covariates, such as local community characteristics, agency practices, and regional subcultures. These residual patterns can guide the direction of future research.

Following the discussion above, state-level aggregated data in which observations are grouped by relatively short time periods will be considered in the present study. Such data can provide enough observations and reduce excess zero counts, with an acceptable level of within-unit heterogeneity. A pooled time series structure of the data can efficiently detect the effect of temporally varying factors. A spatial-temporal mapping analysis can be used to control for the excess variations due to the autocorrelations in space and time.

CHAPTER FIVE DATA AND METHOD

5.1 THE DATA

The data comprises state-level aggregated summaries across the 48 continental states from 1972 to 2003. Recall that the 1970s and 1980s captured the “radical” stage of deinstitutionalization in which younger, more male, and more racially diverse inpatients were rapidly discharged into communities than during the previous “non-radical” stage (Mechanic & Rochefort, 1990; Rapheal & Stoll, 2013)⁶. Thus, it is more meaningful to choose this period of time than the whole time span of deinstitutionalization to explore its impact on the safety risk for police.

Outcome measure

The number of law enforcement officers murdered in the line of duty is chosen as the measure of the safety risk for the police. The data for the dependent variable, the number of law enforcement officers feloniously killed in the line of duty in each state, are from Kaminski (2007) and LEOKA reports (LEOKA, 1997-2003). The death tolls include all local, state, and federal law enforcement officers with arrest power who were murdered in each state. Officers who died during the September 11, 2001 terrorist attacks were excluded. Because the District of Columbia is unique in terms of area size and agency

⁶ As discussed in Chapter 2, at the beginning of deinstitutionalization (the non-radical stage), the psychiatric inpatients who posed less of a public safety concern, or those who had better community support resources, e.g., the elderly /female/mainly white patients, constituted the majority of the first wave of those released. When deinstitutionalization progressed to the radical stage, more inpatients were rapidly discharged to the community due to liberal political motivations and budget-saving orientations. This led to a younger, more male and more minority-predominant discharged population.

structures, it is excluded from the analysis. Due to their distinctive spatial characteristics, the states of Alaska and Hawaii are excluded as well. The outcome variable is named DEATH in the models. There are a total of 1536 observations, the minimum value is 0, the maximum value is 18, the mean count is 1.559, and the standard deviation is 2.173. The distribution of the outcome is illustrated in Figure 5.1a. In addition to the annual data, to explore the potential influence of the variation in temporal aggregations on the estimations of the parameters, the data is grouped into two-year and four-year periods as well. The distributions of killings of law enforcement officers using two-year and four-year time units are displayed in Figure 5.1b and Figure 5.1c, respectively. When using annual data, the zero counts take up about 43% of the total observations. Grouping data into a longer time span decreases the proportion of zeroes (28.26% in two-year period data and 16.41% in four-year period data, respectively). In addition, the longer temporal aggregation makes it easier to illustrate spatial and temporal trends. However, a longer time span could also introduce more within-unit heterogeneities in the related risk factors in each time unit, thus it could affect the estimation of the effect of these predictors. Therefore, it is necessary to test the sensitivity of the analysis to choosing different temporal aggregate units.

Even when using four-year-period data, there still are many zero observations (16.4%). Moreover, the distribution of the outcome is suggestive of two different types of zeroes. For certain states, police murders did not happen at all in most time periods (i.e., Delaware, Rhode Island, Vermont, etc.). As will be discussed later, zero-inflated or hurdle models can be considered to see if they can improve the model fit.

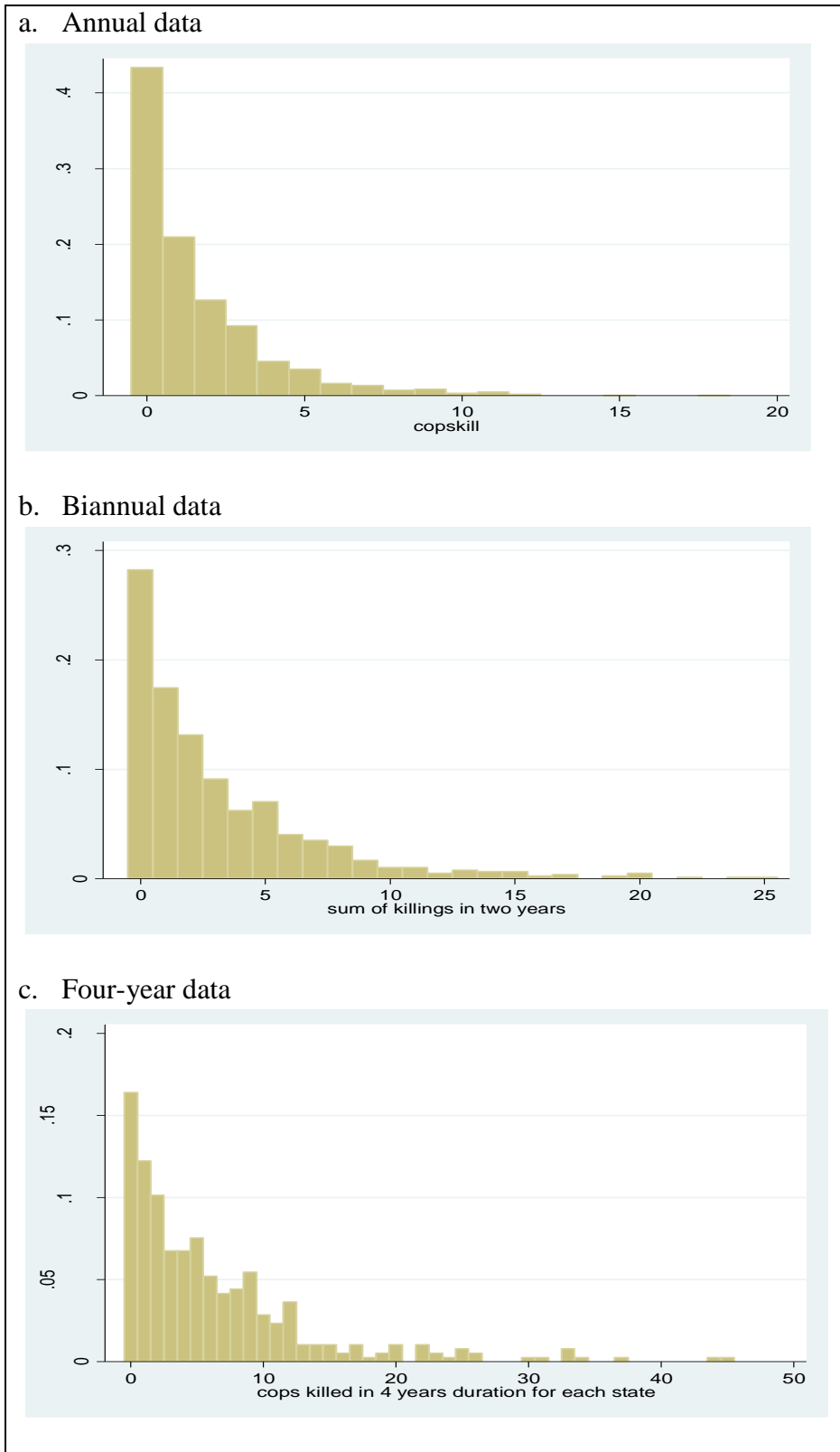


Figure 5.1 Histogram graph of the number of police officer murdered, 1972 – 2003

When modeling count variable, an offset should be used to control for unequal exposure (i.e., unequal length periods, unequal sized populations). An ideal offset in this study would be the numbers of sworn officers per state over time who represent the populations at risk. There are several possible sources for officer employment information: 1) the Police Employee Data from the LEOKA program, which is part of the annual Uniform Crime Reports (UCR); 2) the Annual Survey of Public Employment and Payroll (ASPEP) from the Bureau of the Census (BC); 3) the Census of State and Local Law Enforcement Agencies (CSLLEA) from the Bureau of Justice Statistics (BJS), and 4) the Occupational Employment Statistics (OES) from the Bureau of Labor Statistics (BLS). However, none of these sources can provide reliable data for employed officers for all the time periods in question. For example, the Census data contains some missing data and has obvious errors in early years; the definition of a law enforcement officer used in CSLLEA/BJS data and its predecessors changed several times; the LEOKA/UCR data did not include all law enforcement agencies in the US; and the OES/BLS data are not available before 1987. Therefore, some prior studies use state populations as an offset (Kaminski et al., 2000; Kaminski & Marvell, 2002). Considering that the number of officers employed should be proportional to state populations, state population would be a reasonable alternative to the number of sworn officers, and is adopted as an offset variable in the present study.

As will be discussed later, the relative risks of fatal victimization rather than the observed counts are typically modeled in spatio-temporal analyses.⁷ Since a standardized

⁷ In Poisson regression, the outcome count Y_{it} is usually modeled as $\ln(Y_{it}) = \ln(\text{population}_{it}) + x'_{it}\beta$, where population_{it} is the offset, x'_{it} is the vector of covariates of state i at year t , and β denotes the vector of the corresponding coefficients. However, in WinBUGS and several R packages widely used for spatial analysis, the model is estimated as $\ln(Y_{it}) = \ln(E_{it}) + x'_{it}\beta$, where E_{it} is the expected

mortality ratio (SMR) is an estimate of a relative risk (Lawson, 2003, p. 4), the SMRs for each state at each time period are calculated. An SMR is defined as the observed counts of murdered police officers divided by the expected number of police homicides within each state and time period:

$$SMR_{it} = \frac{Y_{it}}{E_{it}}$$

where Y_{it} and E_{it} are the observed counts and the expected counts for state i and time t , respectively. The expected number of police homicides for state i and time period t is calculated as the total police homicide numbers divided by the average total US population (excluding those in Alaska, Hawaii, and D.C.), and multiplied by this state's average population during the time periods in question:

$$E_{it} = \frac{TotalCount}{USPop} * population_i$$

where *TotalCount* denotes the total number of the killings of officers during the time periods in question, *USPop* is the average total population in the US in these periods, and *population_i* represents the average population for state i in these periods. Therefore, the SMRs represent raw (unconditional) estimations of officers' risks of fatal victimization. To briefly present the spatio-temporal profile of the fatal risks for police, the SMRs in the period in question using four-year data are mapped in Figure 5.2.

According to Figure 5.2, the risks for police of being murdered indicate some spatio-temporal variations. It appears that the police risk of homicide victimization decreased over time in general, but such decreasing trends are not consistent across the

outcome counts. It can be rearranged as $\ln\left(\frac{Y_{it}}{E_{it}}\right) = x'_{it} \beta$, where $\frac{Y_{it}}{E_{it}}$ is simply the SMR_{it} , which is the estimate of the relative risk θ_{it} . E_{it} is calculated by $E_{it} = population_{it} * R$, where R is the overall mortality rate.

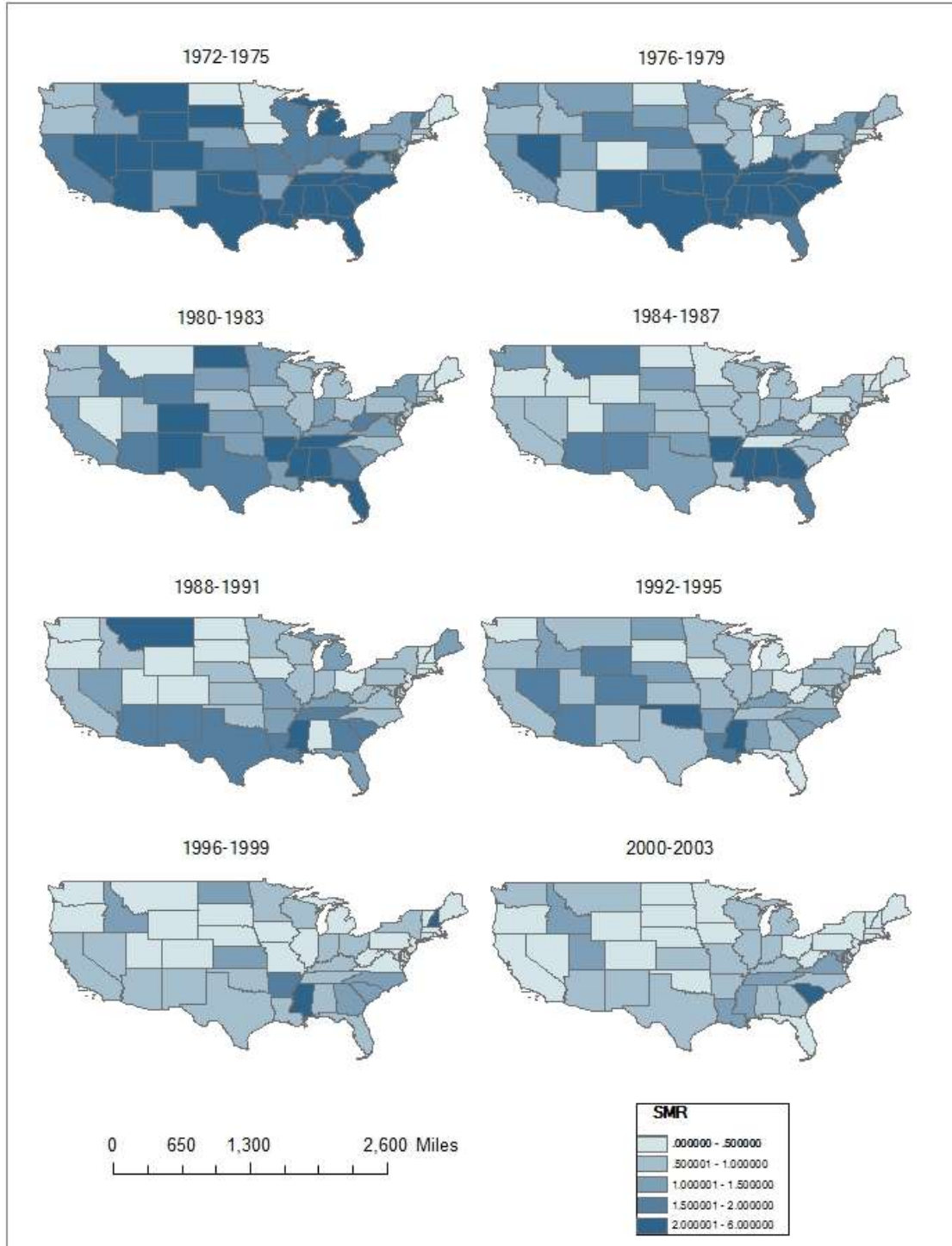


Figure 5.2 The distribution of the SMRs for police murders during 1972-2003, four-year data

48 contiguous states. For instance, the temporal trends of police homicide risks in some west and mid-west states varied from 1972-2003. In each time period, the South tended to be more dangerous to law enforcement officers, but with some temporal variations. Several southeast states had the highest police murder risks during some periods in the 1970s and the 1980s. In contrast, the states on the west coast and in the northeast on average had lower SMRs for police murders than other states across time.

Exposure measure

Data for the major independent variable, the change in institutionalized population, is combined from Harcourt (2011), Raphael (2000), and Salzer and colleagues (2006). Raphael (2000) and Salzer et al. (2006) collected the data based on the Substance Abuse and Mental Health Services Administration's (SAMHSA) annual published reports *Additions and Resident Patients at End of Year, State and County Mental Hospitals, by Age and Diagnosis, by State, United States (Year)*, which recorded inpatient population in public hospitals for each year. Salzer et al. (2006) interpolated data for years where there was missing data or obvious anomalies (i.e., changes of more than 10% compared to the previous year)⁸. Harcourt's study (2011) compiled a data set of hospitalization in public mental hospitals from the Bureau of Census (1934-1946) and National Institute of Mental Health (NIMH, 1947-2001). Regarding the fact that SAMHSA actually evolved from NIMH in the 1970s and took responsibility for providing census data on hospitalization populations from then on, the Harcourt data (2011) can be viewed as a backward extension of Raphael(2000) and Salzer et al. (2006)'s data. The comparison between these three data sets illustrates that there is a strong consistency during their overlapping

⁸ These modifications were accepted by SAMHSA and included in a later publication from them with the corrections (Salzer et al., 2006).

periods⁹. Therefore, the data is combined from these three data sets for the year 1972-2003. Salzer and colleagues' (2006) correction approach is adopted to interpolate missing data and clearly deviant data for data collected before 1984. The change in the institutionalized population is measured by the number of patients released from public hospitals each year. Considering the lag effect of releasing mentally ill patients into the community, this measure is calculated as the difference in the inpatient population in public mental health hospitals between the previous two years. This variable is named as RELEASE RATE, and is entered as a rate – the number released per 100,000 persons (Kaminski, 2007).

Control variables

The control variables are those widely examined in prior police homicide research and are available at the state-level during the time span in question. Their names, descriptions, detailed indicators, and sources are listed as below. The variable names in the model are in parentheses.

RESIDENTIAL STABILITY (STABILITY) is defined as the percentage of the population remaining in the same residence for five years or longer. This measure indicates the stability of the resident population. Data source: Bureau of the Census.

PERCENTAGE OF POPULATION THAT IS BLACK (PERCENT BLACK) denotes the percentage of the resident population that is non-Hispanic black. Following most studies of homicide, this variable is chosen in the present study as the indicator of racial heterogeneity. Data source: Bureau of the Census.

⁹ The census data are continually collected by SAMHSA after 2003, but the method of data collection changed drastically, causing big gaps in some states. Therefore, the data is not comparable to the previous three data sets. Therefore, I decided not to use that data set in this paper.

FEMALE SINGLE PARENT (FEMALE HEADED) is the percentage of female householders living with related children. This variable represents the degree of family disintegration. Data source: Bureau of the Census.

POPULATION DENSITY (POP DENSITY) is defined as the number of residents per square mile for each state. A high population density implies diminished social control and an elevated criminogenic environment. Data source: Bureau of the Census.

AGE STRUCTURE (AGE STRUCTURE) is measured as the percentage of the male residential population that is aged 15-34. This is also an indicator of criminogenic environment, as a large proportion of young males in the population is associated with a heightened level of deviances and crimes. Data source: Bureau of the Census.

VIOLENT CRIME RATES (VIOLENT CRIME) is an indicator of the potential for violence in an area, which influences the proximity of officers to potentially motivated offenders. This variable is measured by the rates of murder and non-negligent homicides, aggravated assaults, and robberies. Data source: FBI's Uniform Crime Reports (UCR)

ECONOMIC DEPRIVATION (ECO DEPRIVATION) is a combined index of poverty rates, median household income, and unemployment rates, which reflects the extent of economic disadvantages. Because these three measures are usually highly correlated with each other, an index measure can be extracted from a principal component analysis (Fridell et al., 2009; Land et al., 1990; Kaminski, 2002; Kaminski & Stucky, 2009; Kaminski, 2008).¹⁰ Data source for poverty rate, median household income, and unemployment rate: Bureau of the Census.

¹⁰ Poverty rate is the percentage of a population living below the official poverty line. Median household income refers to the household income level compared to which half of households earn more and half of households earn less. Unemployment rate is the percentage of the population age 16 and over unemployed.

GINI (GINI) refers to the income distribution of residents, and is used to identify the inequality between the rich and the poor. This variable is included in the model as a measure of relative economic deprivation.¹¹ Data source: Bureau of the Census.

INCARCERATION RATES (INCARCERATION) denotes the incarceration rates, which are closely related to both police homicides and the change in the psychiatric institutionalized population¹². Incarceration rate is calculated by the number of persons with a sentence of more than one year in state or federal prison divided by the population (in 100,000 persons) in each state. Data source: Bureau of Justice Statistics.

Similarly, all the annual data are also grouped into two-year and four-year periods. For two-year and four-year data, the averages for each time period are calculated respectively. Summary statistics for the dependent and independent variables using annual data appear in Table 5.1. The unconditional variance of the outcome variable (4.722) is much larger than its unconditional mean (1.559), implying the possibility of overdispersion. An overdispersion test is then conducted through the AER package in R after fitting the outcome with covariates in a generalized linear model (glm) regression. The result provides evidence of overdispersion ($\alpha=0.584$, $p<.0001$)¹³. A negative binomial model could be considered to see if it could improve the fit in comparison with Poisson models.

¹¹ The calculation formula of GINI index with N elements ordered from the poorest to the richest is $Gini = \sum_{j=1}^N 2(X_j - Y_j)\Delta X_j$, where $X_j = I/N$, $Y_j =$ cumulative percentage of income by unit, and $\Delta X_j = X_j - X_{j-1}$.

¹² See the discussions in section 2.2 and section 4.2.

¹³ When using the “trafo=1” option in AER, a value of alpha larger than zero indicates overdispersion.

Table 5.1. Summary statistics for variables used in the analysis (N=1,536).

Variables	Min	Max	Mean	SD
DEATH	0	18	1.56	2.17
RELEASE RATE	-41.04	115.72	3.69	7.94
STABILITY	32.34	64.22	51.63	6.06
BLACKPCT	.20	36.62	9.70	9.31
FEMALE HEADED	3.92	12.60	7.26	1.59
POP DENSITY	3.71	1152.74	168.24	235.77
AGESTRUCTURE	16.83	39.52	29.82	4.09
VIOLENT CRIME	40.18	1184.58	413.02	228.27
ECO DEPRIVATION	-3.67	4.84	6.89e-10	1.37
GINI	0.32	0.47	0.38	.03
INCARCERATION	20.34	801.20	223.77	149.10

5.2 ANALYSIS PLAN

Solutions for collinearity issue

In studies using eco-social structural factors as regressors, collinearity is not unusual (Land, McCall, & Cohen 1990). Correlation matrices and collinearity tests for each wave of the data do show signs of collinearity¹⁴. Conducting a principal component analysis (PCA) is a common way to reduce collinearity. However, due to the longitudinal nature of this proposed data, a PCA which does not consider the temporal autocorrelations may not be the best choice. Fortunately, although collinearity could make the estimation of the effects of the variables that are collinear less precise (i.e., unstable estimates or increased variance), it does not influence the performance of the whole model. Also, as long as the main variables of interest are not highly collinear with these control variables, the estimation of the main variables' effects would not be impacted (Allison, 2012). The correlation matrices show that the main exposure variable, the release rate of the inpatient

¹⁴ Correlation matrices are examined and collinearity tests are conducted to check if collinearity problems exist. The variance inflation factors (VIF) and the Conditioned Indices (CI) are computed for each wave of data. Values of VIF greater than 10 suggest collinearity. Values of CI larger than 30 imply collinearity. The results of the collinearity tests and correlation matrices for selected time periods are provided in Appendix A.

psychiatric population, only has weak correlations with other predictors (except for moderate correlations with residential mobility or population density in one or two waves of the data). The variance inflation factors (VIF) of this variable vary from 1.13 to 1.64 across eight time periods. It would be safe to examine the effect of this variable without considering collinearity. Furthermore, a technique of residualization is used to make sure the estimation of some other important regressors, such as violent crime rates (VIOLENT CRIME) and incarceration rates (INCARCERATION), are minimally affected by the collinearity issue. Residualization refers to a method for disentangling the effects of the predictors which are correlated with each other. To do this, one predictor is regressed on other correlated predictors (e.g., using STABILITY, BLACKPCT, FEMALEHEADED, POPDENSITY, ECODEPRIVATION, and GINI to predict VIOLENT CRIME). The residuals from this regression produce a new predictor variable (e.g., $CRIME_{resid}$). This new variable ($CRIME_{resid}$) has no correlations with those predictors, and can be used in the subsequent analysis. This new predictor, which represents the residual variations in VIOLENT CRIME unexplained by other predictors, will be included in the regression (Roncek, 1997).

Analysis models

Bayesian hierarchical modeling techniques were used to accommodate the geographical and temporal autocorrelation in the analysis. Although Bayesian modelling has gained increased attention in recent years in the criminal justice field (Law & Haining, 2004; Law & Quick, 2012; Law, Quick, & Chan, 2014; Yu et al., 2008), this relatively new analysis approach has not been used in the study of violence against police before. Briefly, while traditional frequentists view the parameters of the examined distributions

as fixed, Bayesians believe these parameters also have their own distributions. The likelihood of observed data combined with researchers' prior beliefs can be used to compute the posterior distribution of these parameters (Greenland, 2006)¹⁵. In the analysis of space-time referenced data, the distinct advantage of Bayesian hierarchical modeling over the traditional frequentist approach is that the former can easily combine certain spatial or temporal priors and hyperprior beliefs (distributions)¹⁶ in a hierarchical manner to incorporate geographical and time series information into the model (Carlin & Louis, 2000; Waller, Carlin, Xia, & Gelfand, 1997).

As noted in the previous section, in the analysis of data involving spatial and temporal dimensions, some statistical approaches need to be applied to deal with the issues of dependences and the variations in space and time. The geographical or time-series dependence (i.e., spatial and temporal autocorrelation) might exist because the outcome values in any given region or time point could be influenced by its neighboring areas or time periods. This correlation comes from the similarities in these adjacent areas and time periods, which are usually unobservable or unmeasurable (Knorr-Held & Besag, 1998). If an analysis fails to control for the variations introduced by spatial and temporal autocorrelations, it could yield misleading risk assessments and unstable coefficient estimates. Also, when the incident is rare, zero and low counts

¹⁵ The prior belief or prior distribution is the researcher's subjective belief about the distribution of the unknown parameters of interest. It comes from what the researcher knows or expects based on existing knowledge. The likelihood is the probability of the unknown parameters given observed data. The posterior distribution is the updated belief about the distribution of the unknown parameters after combining the prior belief and the likelihood. It is essentially what we believe about the unknown parameters after observing sampled data. The relationship between these three parts can be expressed as: prior x likelihood = posterior (Greenland, 2006).

¹⁶ In Bayesian statistics, a parameter of a prior distribution can have its own prior distribution. Such a distribution is called a hyperprior distribution. For example, in a random effect model, the random effect is assumed to follow a normal distribution with a mean 0 and a variance δ^2 . This normal distribution is called prior distribution. However, the variance δ^2 of the random effect can also have its own prior distribution, e.g., a Gamma distribution. This Gamma distribution is then called hyperprior. Therefore, a hyperprior is a prior on a parameter of a prior.

usually dominate the data. A raw mapping of incident rates is not an accurate reflection of the risk estimates, i.e., zero counts do not mean zero risks. Moreover, individual extreme values could distort the risk estimates markedly in rare event cases, especially for those areas with small population sizes. Such “noise” covers the “true patterns of underlying risk” (Richardson, Abellan, & Best, 2006: 386). Therefore, some type of smoothing, which means borrowing information from neighboring observed units, should be considered to take these issues into account (Knorr-Held & Besag, 1998). Specific spatial or temporal smoothing prior distributions, such as the conditional autoregressive model (CAR) and the random walk process (which will be discussed later) have been widely applied in practice so that the Bayesian hierarchical modeling strategy can easily deal with geographical and temporal trend variations at the same time.

Model structure

In this study, let $DEATH_{it}$ denote the number of felonious killings of officers for state i at time interval t , where $i=1, \dots, 48$ and $t=1, \dots, 8$. It is usually assumed that the rare event outcome follows a Poisson distribution as $DEATH_{it} \sim \text{Pois}(E_{it}\theta_{it})$, where E_{it} is the expected count and θ_{it} is the relative risk in the i^{th} state and t^{th} time interval. Then the basic structure of the model can be written as simple log-linear Poisson model

$$\ln(\theta_{it}) = \mathbf{x}'_{it}\boldsymbol{\beta}$$

where \mathbf{x}'_{it} is the vector of independent variables of state i at period t , and $\boldsymbol{\beta}$ denotes the vector of the corresponding coefficients¹⁷. When the data involving space and time information, a classic spatio-temporal model can be expressed as:

$$\ln(\theta_{it}) = \mathbf{x}'_{it}\boldsymbol{\beta} + u_i + v_i + \delta_t + \gamma_t + \varphi_{it}$$

¹⁷ $\mathbf{x}'_{it}\boldsymbol{\beta}$ is the matrix form of the linear regression which is equivalent to $\beta_0 + x_{it1}\beta_1 + \dots + x_{itp}\beta_p$, where x_{itk} ($1 \leq k \leq p$) denote the independent variables, β_k ($1 \leq k \leq p$) are the correspondent coefficients.

where u_i represents the unstructured spatial random effect for state i , v_i is a structured spatial element for state i , δ_t denotes the structured variation for year t coming from temporal autocorrelation, γ_t is the unstructured temporal random effect, and φ_{it} represents the additional time-space interaction random effect. Therefore, this model captures the heterogeneity due to unstructured spatial variability (spatial random effect), the spatial dependence among adjacent states, the temporal autocorrelation between the values of outcome in the current and previous time periods, the unstructured temporal variation (temporal random effect), and the interaction effects between space and time variations (Cai et al., 2013; Knorr-Held, 2000). Using specific comparison measures, the performances of the models using different combinations of these random effects can be evaluated.

Moreover, when the observations span across a long time period or multiple spatial units, the assumption that the effects of the risk factors are fixed across time or space might be too rigid. To relax this assumption, a random slope model incorporating temporal or spatial autocorrelation structures could be also considered. For example, suppose the regression model has only one predictor; and the effect of this predictor (x_{1it}) is temporally or spatially varied, the model can be written as

$$\ln(\theta_{it}) = \beta_{0it} + \beta_{1it}x_{1it}$$

$$\beta_{0it} = b_0 + v_{0it}$$

$$\beta_{1it} = b_1 + v_{1it}$$

where β_{0it} is the random intercept, which includes a global intercept, b_0 , and a random component, v_{0it} . Similarly, β_{1it} is the random slope of this predictor, which includes a

globe effect, b_1 , and a random effect, v_{1it} . Both v_{0it} and v_{1it} could include spatial or temporal components (Blangiardo & Cameletti, 2015)¹⁸.

Overdispersion is very common in count data, which violates the assumption of Poisson distribution (i.e., that the variance is equal to the mean). In such circumstances a negative binomial may be applied. As illustrated earlier, there is an overdispersion issue in the current data (See Table 5.1 and the related overdispersion test). A negative binomial model is then considered to see if it could improve the model fit in comparison to the Poisson model. Using this model, the distribution of an observed count $DEATH_{it}$ is

$$DEATH_{it} \sim \text{NegBin}(E_{it}\theta_{it}, \alpha),$$

where E_{it} is the expected count, θ_{it} is the relative risk in the i^{th} state and t^{th} year, and α is the overdispersion parameter. The mean of the distribution is $E_{it}\theta_{it}$, and the variance is $E_{it}\theta_{it} \left(1 + \frac{E_{it}\theta_{it}}{\alpha}\right)$. Note if $\alpha \rightarrow \infty$ then the distribution is reduced to a regular Poisson. The parameter θ_{it} is modeled the same way as in the previous Poisson model. A Gamma prior is assigned to α , as α has to be positive.

As indicated in the histogram of the respondent variable (Figure 5.1), there were a large number of zero outcome observations in the data. The previous count models may not fit well in zero-dominated data. Therefore, it is worth considering zero-inflated count models to account for the issue of excess zeroes. Instead of assuming all the zeroes come from the same data-generating process in which the nonzero observations were produced, zero-inflated models assume that these zero counts could have been generated through

¹⁸ For example, it could be $v_{0it} = u_{0i} + v_{0i} + \delta_{0t}$, and $v_{1it} = u_{1i} + v_{1i} + \delta_{1t}$, where u_{0i} , v_{0i} , and δ_{0t} are the unstructured and structured spatial and temporal correlation terms at the global level, and u_{1i} , v_{1i} , and δ_{1t} represent the unstructured and structured spatial and temporal correlation components for the predictor x_{1it} .

two different processes: Only a portion of zeroes (sampling zeroes) comes from the count model which also produced all other positive observations, while another process yields structural zeroes. Whether a zero observation belongs to structural zeroes or sampling zeroes is determined by a Bernoulli process (Lambert, 1992; Greene, 1994). Hence, a general structure of a zero-inflated count model is

$$\begin{cases} \Pr(y = 0) = (1 - p) + p * f(y = 0), \text{ if count is a zero.} \\ \Pr(y = k) = p * f(y = k), \text{ if count is any positive integer } k. \end{cases}$$

where p is the probability that a zero observation is a sampling zero, and $f(y)$ could be a Poisson or a negative binomial model. The parameter p can be estimated through a logistic regression.

The zero-inflated Poisson (ZIP) model is then expressed as

$$\begin{cases} \Pr(\text{DEATH}_{it} = 0) = (1 - p_{it}) + p_{it} * \text{Pois}(\text{DEATH}_{it} = 0) \\ \Pr(\text{DEATH}_{it} = k) = p_{it} * \text{Pois}(\text{DEATH}_{it} = k), \quad k > 0 \end{cases}$$

where p_{it} represents the probability that a zero observation is a sampling zero at state i and time t . The relative risk, θ_{it} , in the Poisson part can be modeled as introduced in the previous Poisson model. The probability that a zero count belongs to sampling zeroes, p_{it} , can be modeled as

$$\text{logit}(p_{it}) = \mathbf{c}'_{it} \boldsymbol{\gamma}_{it}$$

where \mathbf{c}'_{it} represents the vector of variables (including the intercept) for predicting p_{it} at state i and time period t , and $\boldsymbol{\gamma}_{it}$ denotes the vector of the corresponding coefficients.

Theoretically, \mathbf{c}'_{it} could use the same set or different sets of predictors used in the Poisson model, but due to the limitation of the statistics software used (the INLA package

in R), this study only includes the intercept in the logistic model to predict whether a zero is a structural zero.

Similarly, a negative binomial model with zero-inflated structure can be fitted (ZINB model). The model is written as

$$\begin{cases} \Pr(\text{Death}_{it} = 0) = (1 - p_{it}) + p_{it} * \text{NegBin}(\text{Death}_{it} = 0) \\ \Pr(\text{Death}_{it} = k) = p_{it} * \text{NegBin}(\text{Death}_{it} = k), \quad k > 0 \end{cases}$$

The probability that a zero observation is a sampling zero at state i and time t , p_{it} , is estimated in the same way as in the ZIP model. The relative risk, θ_{it} , and the overdispersion term, α , in the negative binomial part can be modeled as introduced in Model 2.

The selection of prior and hyperprior distribution

A Bayesian hierarchical modelling approach is adopted in this study. After assembling the basic components of the models at the first stage, the next step is to assign specific prior distributions to these model components.

For the coefficients of the independent variables (β s), since there are no consistently confirmed findings on the effects of these predictors (see Kaminski & Marvell, 2002), a proper and vague prior (i.e., a normal distribution), is preferred. Hence, a commonly used Normal (0, 10,000) is assigned to these coefficients. Similar to the traditional multi-level model, the unstructured spatial effects are treated as random effects which follow a normal distribution with mean 0 and variance σ_u^2 respectively. For the spatial structured random effect, A widely used intrinsic conditional autoregressive model (ICAR) prior is adopted (Besag, York, & Mollie, 1991)

$$[v_i | v_j, j \neq i, \sigma_v^2] \sim \text{Normal}\left(\frac{1}{m_i} \sum_{j \neq i} w_{ij} v_j, \frac{1}{m_i} \sigma_v^2\right)$$

where m_i is the number of the neighboring states of state i , $w_{ij}=1$ if i and j are adjacent states, and $w_{ij}=0$ otherwise. Hence, assuming an ICAR, the mean of state i is smoothed as the average of the means of its neighbor states¹⁹, and the variance is the variance of v_i divided by the number of adjacent states. A random walk process in which $\delta_t \sim Normal(\delta_{t-1}, \sigma_\delta^2)$ is chosen to represent the temporal autocorrelations between the outcome value in the current time period and the one in the previous time period (Clayton, 1996; Knorr-Held, 2000). A random walk process is a special case of first-order time series autocorrelation prior, $AR(1)$. By using this prior, the current value of the outcome is assumed to follow a normal distribution centered at the previous outcome value with variance, σ_δ^2 . For σ_u^2, σ_v^2 , and σ_δ^2 , since they have to be positive and there is no prior knowledge about them, a hyper-prior distribution Inverse-Gamma (0.001, 0.001), which allows wide variations in these parameters (Spiegelhalter, Best, Carlin, & van der Linde, 2002), is used. A Gamma (0.01, 0.01) is assigned to α for the negative binomial model (Neelon, Chang, Ling, & Hastings, 2014).

Model computation and comparison

For model comparison purposes, four Bayesian hierarchical spatio-temporal models (Models 1-4) adopting Poisson or Negative Binomial distribution with and without zero-inflated structures are to be estimated. Posterior computation is processed by the INLA packages in R. INLA stands for Integrated Nested Laplace Approximation, which is an alternative approach to the classic Markov Chain Monte Carlo (MCMC) method for fitting Bayesian models (Rue, Martino & Chopin, 2009). Compared to MCMC, INLA can fit spatio-temporal models faster, process high-dimensional data more efficiently, and

¹⁹ Following the widely used definition in health spatial research, two states are defined as neighbors as long as they have common borders, including a point.

handle random effects more easily (Lawson, 2013).

After fitting these count variable models, deviance information criterion (DIC), proposed by Spiegelhalter and colleagues (2002), can be used to evaluate which model fits the data the best. DIC is defined as $DIC = \bar{D} + P_D$, which is a combination of \bar{D} , a summarized measure of the current model fit, and P_D , a penalty of the model complexity.

Smaller values of DIC indicate better fittings of the model. P_D is calculated as

$$P_D = E_{\theta|y}(D) - D(E_{\theta|y}(\theta)) = \bar{D} - D(\bar{\theta}), \text{ where } \bar{D} = E_{\theta|y}(D) \text{ and } D(\theta) = -2 \log p(y|\theta) + 2 \log f(y).$$

Also, the negative cross-validated predictive log-likelihood (NLLK) based on the Conditional Predictive Ordinate (CPO) (Gelfand & Dey, 1994; Gesser, 1993; Dey et al., 1997; Spiegelhalter et al., 1996) is employed to compare the prediction performance among these models. The CPO is the density of the posterior predictive distribution evaluated at an observation, given the data excluding the information of this observation. Hence, the CPO is a cross-validation measure. The NLLK is the negative summation of the logs of CPOs. A lower NLLK indicates a better fit.²⁰

²⁰ The CPO for state i and time t is defined as

$$CPO_{it} = f(Y_{it} | \mathbf{Y}_{-it}) = \int f(Y_{it} | \boldsymbol{\theta}, \mathbf{Y}_{-it}) f(\boldsymbol{\theta} | \mathbf{Y}_{-it}) d\boldsymbol{\theta} = \left(\int \frac{1}{p(Y_{it} | \boldsymbol{\theta})} P(\boldsymbol{\theta} | \mathbf{Y}) d\boldsymbol{\theta} \right)^{-1},$$

where \mathbf{Y}_{-it} denotes the vector of police murder observations excluding Y_{it} and $\boldsymbol{\theta}$ is the vector of unknown parameters. The cross-validation likelihood as a summary measure is then calculated as

$L_{cv} = \prod_{i=1}^n \prod_{t=1}^T CPO_{it}$. A larger L_{cv} implies a better fit. Usually, the values of L_{cv} s are very close to zero.

Therefore, the negative cross-validated log-likelihood can be used for model comparison:

$NLLK_{cv} = - \sum_{i=1}^n \sum_{t=1}^T \log CPO_{it}$. Thus, a lower $NLLK_{cv}$ indicates a better fit, which is consistent with other

main model comparison criteria. The estimate of the CPO_{it} can be obtained by $\widehat{CPO}_{it} = \frac{1}{\frac{1}{T} \sum_{t=1}^T [P(Y_{it} | \theta^{(t)})]^{-1}}$,

where T is the number of samples drawn from the MCMC chain, and $\theta^{(t)}$ is the number t MCMC sample.

CHAPTER SIX

RESULTS

6.1 MODEL ESTIMATION

The raw data was collected on an annual basis. To test the sensitivity of the analysis to using different levels of aggregate temporal units, the data aggregated in different time periods (annual, two-year, and four-year data) will be analyzed respectively. The analysis begins with the one-year data. Since the data is temporally referenced, the first step is to check whether there is a temporal trend in terms of the outcome. To do so, the annual SMRs (left panel) and the logs of the SMRs (right panel) are plotted against time. The plots are displayed in Figure 6.1. It appears that the raw SMRs decreased over time in Figure 6.1. This decreasing trend becomes more obvious when plotting the log transformed SMRs against years. This pattern is consistent with the downward trend of police risk of homicide victimization since the early 1970s observed in Figure 5.2. This trend was also reported by Kaminski and Marvell (2002).

Next, the lattice plots (Figure 6.2) of the log of SMRs against year for each state are used to inspect whether such temporal trends varied across states. According to Figure 6.2, the temporal variations in the risks of police homicide were not consistent among the 48 continental states. While the majority of these states showed similar decreasing trends over time, some individual states (i.e, Idaho, Kansas, and Mississippi) did not illustrate

any patterns. This finding implies that a space-time interaction term might need to be included in the model to explain these deviations from the general trend.

The time variable could be added in the model as a linear predictor to capture the temporal variations in the fatal risks for police. However, it would be meaningless if there were no theoretical basis to do so. The temporal changes in the outcome risks could actually be the effects of other temporally varied risk factors (i.e., crime levels, incarceration rates). Alternatively, the time variable could also be used as a temporal random effect in the proposed model, which only represents the temporal autocorrelation structures. As will be discussed later, we can numerically test which method can provide a better fit by using model comparison measures.

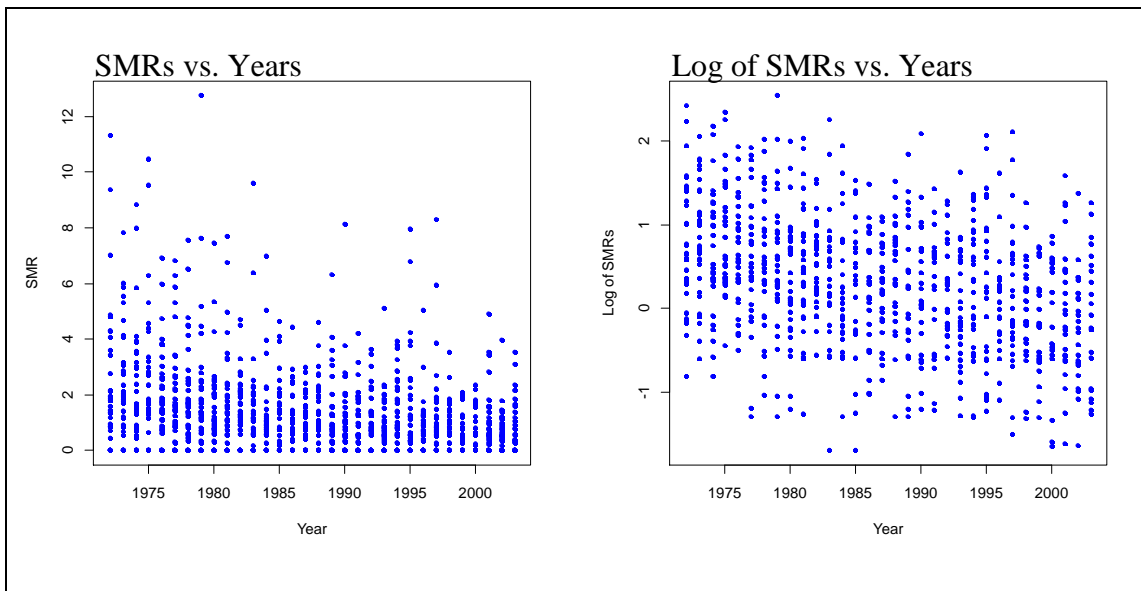


Figure 6.1 Scatter plots of the SMRs vs. Years

Notes: There are some missing values of the log of the SMRs due to zero count.

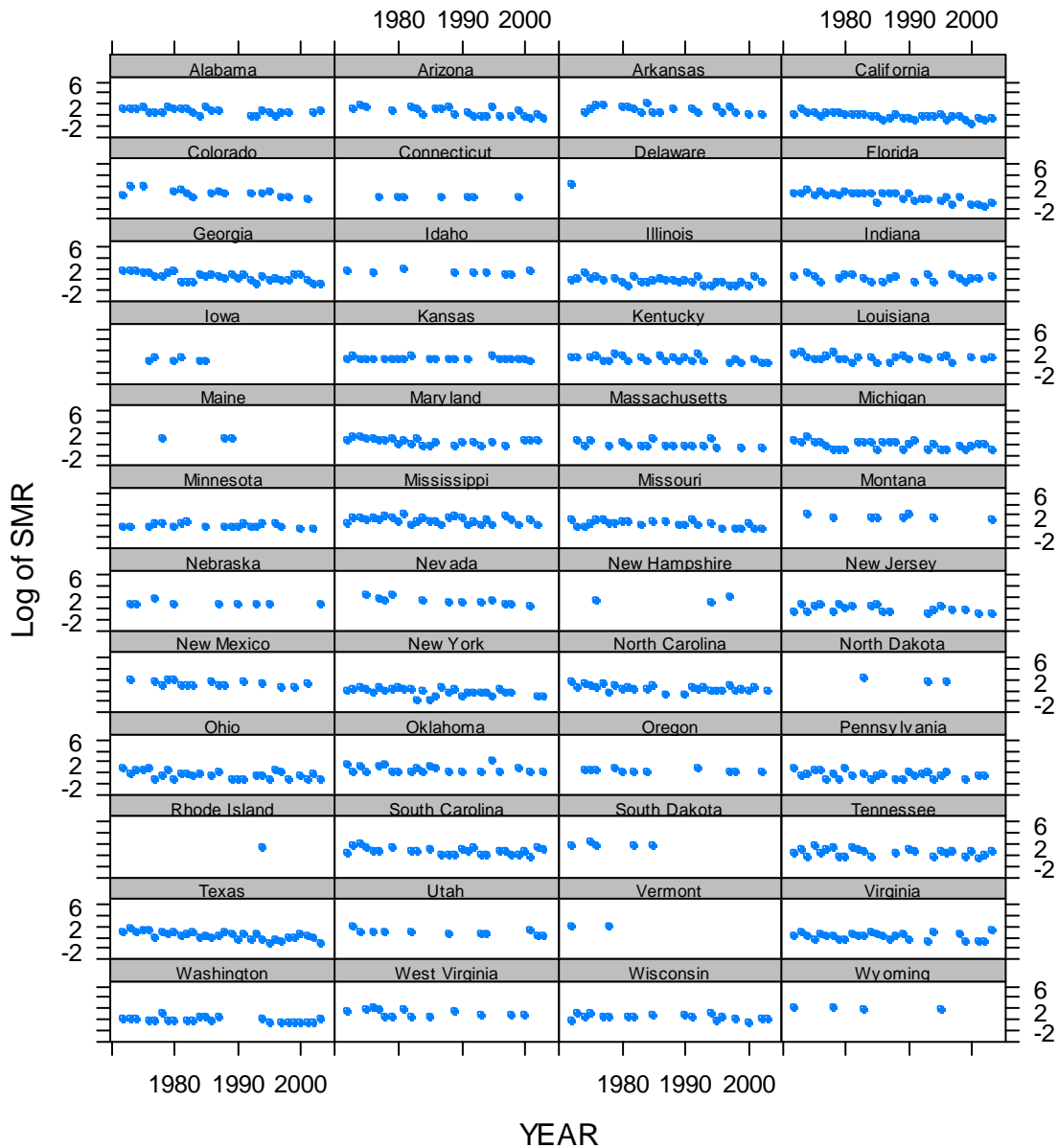


Figure 6.2 Lattice plots of the log of SMRs against year for each state
Notes: There are some missing values of the log of the SMRs due to zero count.

Furthermore, a visual inspection of the bivariate relationship between the outcome and the major exposure is conducted to get a general idea of their connections. The plots of the SMRs (left panel) and the logs of SMRs (right panel) against the mental health inpatients' release rates are presented in Figure 6.3. Since the outcome is rare count data,

the plot of the original SMRs against the values of the predictor shows a strange pattern and does not provide much helpful information. When the SMRs are presented in log form, it can be seen that there are a large number of observations clustered in a narrow vertical direction area above the x-axis. It is probably caused by the much lower discharge rates after the 1990s, compared to that in the previous years. Generally, the plot shows a somewhat positive correlation between the log of the SMRs and the discharge rates, but the cluster mentioned above implies that some heterogeneity existed over time, which could influence the correlation between these two variables. However, this plot does not suggest any sign of a polynomial relationship between these two variables, thus indicating it is sufficient to use the SMRs as the linear regressor at this stage.

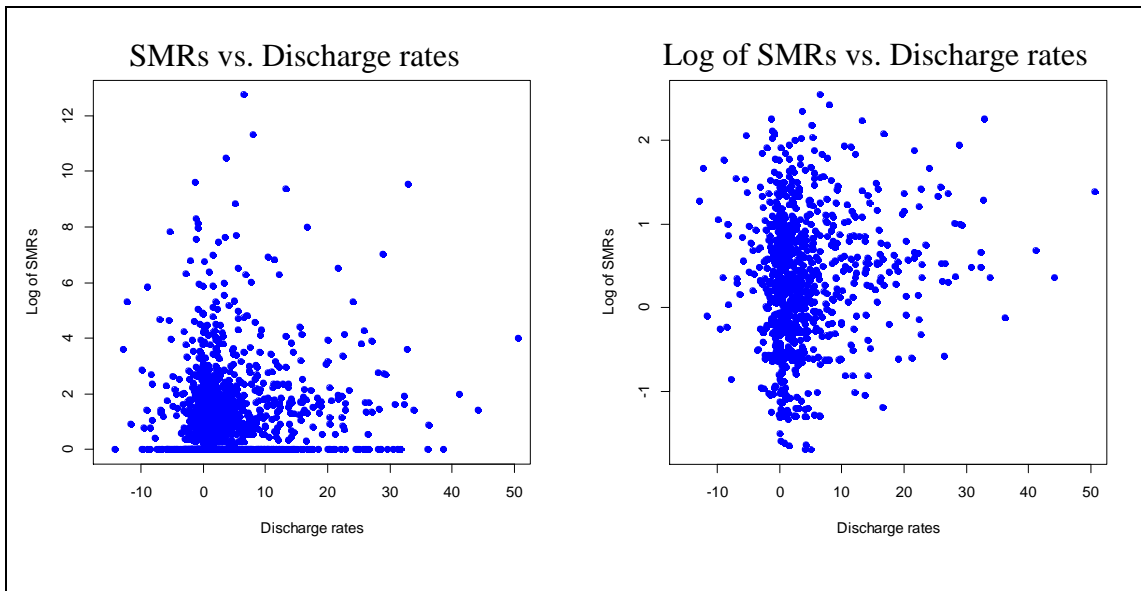


Figure 6.3 Scatter plots of the SMRs and the discharge rates

Notes: There are some missing values of the log of the SMRs due to zero count.

A preliminary numerical assessment of the relationship between the exposure variable and the outcome is then made by estimating a series of bivariate regression models (Models 1-3). The results of these models are displayed in Table 6.1. Without

considering temporal autocorrelations, a naïve cross-sectional model (Model 1) finds that the risks for police homicides were significantly positively related to the change in the hospitalized mentally ill population. This result is in accordance with the visual impression obtained from above plots. However, when taking the temporal effect into account, by treating it either as a random walk temporal effect (Model 2) or as a linear trend predictor (Model 3), this positive association between the exposure and the outcome disappears. As discussed in the previous chapter, the performance of these models should be assessed by specific model comparison measures. DIC and NLLK are two popular criteria among these comparison criteria, and are used in this paper. Both Model 2 and Model 3 provide better model fits than Model 1, as they have lower DIC and NLLK values than Model 1. This result shows the importance of incorporating time factors into the model when analyzing longitudinal data. Ignoring temporal effects could produce misleading findings. In addition, Model 2 has much lower DIC and NLLK values than Model 3, suggesting that using the time variable as a random effect is more appropriate than adding it as a linear predictor.

After the bivariate analyses, the SMRs are regressed on the discharge rates and all the other predictors discussed in the previous chapter through a Bayesian Poisson model. A series of alternative models are fitted to compare their performance. These models include a model that only considers temporal autocorrelation, but no spatial dependence (Model 4), a model incorporating the temporal and unstructured spatial autocorrelation (Model 5), a model including these autocorrelations and structured spatial components (CAR) (Model 6), a model adding unstructured temporal effects (Model 7), a model accommodating a space-time interaction term but dropping the unstructured temporal

Table 6.1 Results for the bivariate Bayesian models

Parameters	Model 1 (Cross-sectional)		Model 2 (Year as a random effect)		Model 3 (Year as a linear predictor)	
	mean	95% CrI	mean	95% CrI	mean	95% CrI
Intercept	-0.0730**	-0.1176, -0.0289	-0.0206	-0.0677, 0.0260	0.6480**	0.5536, 0.7416
RELEASE RATE	0.0172**	0.0133, 0.0208	-0.0036	-0.0092, 0.0019	-0.0012	-0.0065, 0.0039
YEAR					-0.0410**	-0.0461, -0.0360
Model fit						
DIC	4743.73		4103.00		4476.81	
pD	2.04		32.11		3.042	
NLLK	2373.742		2055.082		2239.31	

Notes: **- significant with 95% credible intervals²¹ that do not contain 0; coefficients are not exponentiated.

²¹ A credible interval in Bayesian analysis is equivalent to a confidence interval in frequentist analysis but has a different philosophical interpretation.

term (Model 8), and a model incorporating all structured/unstructured time and space components as well as a time-space interaction random effect (Model 9). The results of these models are presented in Table 6.2.

Note that the credible intervals of the estimated parameters in the model without spatial random effect terms (Model 4) are the narrowest intervals compared to other models. However, this is not a sign of this model's good performance. Instead, some researchers (Barry & Elith, 2006; Beale, Lennon, Yearsley, Brewer, & Elston, 2010; Law & Chan, 2012; Legendre, 1993) have found that the non-spatial analysis methods are prone to Type I errors (rejecting the null hypothesis when it is actually true) when analyzing spatial correlated data. Narrow variances of the estimates tend to find "significant" covariates even when these covariates are in fact not significant. As discussed earlier, DIC and NLLK can be used to assess the performance of these models..

The results show that Model 4 only considering temporal autocorrelation has a DIC of 4153.33 and an NLLK of 2079.36. The DIC and NLLK decrease (4122.38 and 2065.65, respectively) when the unstructured spatial term is added (Model 5), suggesting that the fit of the model is improved by introducing a random spatial effect. The model including both spatial unstructured and structured variation components (Model 6) has slightly decreased DIC (4118.25) and NLLK (2062.94) values. When the unstructured temporal component is added to the model (Model 7), the comparison measures do not drop anymore (DIC = 4118.42, and NLLK = 2063.04), indicating that an unstructured random temporal term is not needed for the current data. However, after space-time interaction components are introduced into the model (Model 8), there are marked drops in the DIC and NLLK values, which are 4089.29 and 2059.01, respectively. This suggests

Table 6.2 Results for the Bayesian models using different temporal/spatial correlation structures

Parameters	Model 4 (δ_t)		Model 5 ($u_i + \delta_t$)		Model 6 ($u_i + v_i + \delta_t$)	
	mean	95% CrI	mean	95% CrI	mean	95% CrI
Intercept	1.3287	-0.1497, 2.7640	2.7362	0.9315, 4.1359	3.1134	1.5802, 4.4220
RELEASE RATE	0.0037	-0.0024, 0.0096	0.0040	-0.0022, 0.0099	0.0045	-0.0017, 0.0104
FEMALE HEADED	0.0096	-0.0356, 0.0990	0.1177**	0.0477, 0.1733	0.1175**	0.0627, 0.1686
POP DENSITY	-0.0006**	-0.0010, -0.0003	-0.0008**	-0.0013, -0.0003	-0.0005	-0.0011, 0.0001
STABILITY	-0.0275**	-0.0377, -0.0171	-0.0392**	-0.0550, -0.0225	-0.0445**	-0.0621, -0.0266
AGE STRUCTURE	-0.0189	-0.0432, 0.0078	-0.0457**	-0.0627, -0.0204	-0.0462**	-0.0619, -0.0272
VIOLENT CRIME	-0.0001	-0.0004, 0.0002	0.0003	-0.0001, 0.0007	0.0002	-0.0001, 0.0006
INCARCERATION	-0.0001	-0.0007, 0.0006	-0.0008*	-0.0014, 0.0000	-0.0008**	-0.0013, -0.0001
ECO DEPRIVATION	0.1211**	0.0647, 0.1766	0.1217**	0.0571, 0.1808	0.1314**	0.0711, 0.1884
GINI	0.4161	-1.7291, 2.6000	-1.0797	-3.2816, 1.4561	-1.2732	-3.4078, 1.0027
PERCENT BLACK	0.0238**	0.0154, 0.0238	0.0199**	0.0091, 0.0310	0.0122	-0.0015, 0.0252
Model fit						
DIC	4153.33		4122.38		4118.25	
pD	18.05		36.80		32.43	
NLLK	2079.356		2065.654		2062.94	

Notes: **- significant with 95% credible intervals that do not contain 0; *- marginally significant with 95% credible intervals that reach 0; coefficients are not exponentiated.

Table 6.2 (Continued)

Parameters	Model 7 ($u_i + v_i + \delta_t + \gamma_t$)		Model 8 ($u_i + v_i + \delta_t + \varphi_{it}$)		Model 9 ($u_i + v_i + \delta_t + \gamma_t + \varphi_{it}$)	
	mean	95% CrI	mean	95% CrI	mean	95% CrI
Intercept	3.1265**	1.6249, 4.4245	3.0884**	1.5719, 4.4766	3.1045**	1.6109, 4.4820
RELEASE RATE	0.0045	-0.0017, 0.0104	0.0049	-0.0017, 0.0113	0.0049	-0.0017, 0.0113
FEMALE HEADED	0.1177**	0.0635, 0.1685	0.1148**	0.0593, 0.1683	0.1151**	0.0603, 0.1683
POP DENSITY	-0.0005	-0.0011, 0.0001	-0.0005	-0.0010, 0.0001	-0.0005	-0.0010, 0.0001
STABILITY	-0.0446**	-0.0621, -0.0268	-0.0448**	-0.0623, -0.0274	-0.0449**	-0.0623, -0.0276
AGE STRUCTURE	-0.0463**	-0.0620, -0.0279	-0.0455**	-0.0624, -0.0268	-0.0457	-0.0624, -0.0273
VIOLENT CRIME	0.0002	-0.0001, 0.0006	0.0002	-0.0002, 0.0006	0.0002	-0.0002, 0.0006
INCARCERATION	-0.0008**	-0.0013, -0.0001	-0.0008**	-0.0014, -0.0001	-0.0008**	-0.0014, -0.0001
ECO DEPRIVATION	0.1320**	0.0719, 0.1889	0.1395**	0.0778, 0.1988	0.1399**	0.0784, 0.1991
GINI	-1.2868	-3.4105, 0.9690	-1.2921	-3.6041, 1.1135	-1.3094	-3.6094, 1.0779
PERCENT BLACK	0.0122	-0.0015, 0.0252	0.0131	-0.0006, 0.0132	0.0130	-0.0005, 0.0259
Model fit						
DIC	4118.42		4089.29		4089.78	
pD	32.58		162.39		160.83	
NLLK	2063.039		2059.014		2059.155	

Notes: ** - significant with 95% credible intervals that do not contain 0; * - marginally significant with 95% credible intervals that reach 0; coefficients are not exponentiated.

that the model fit is significantly improved by adding the spatio-temporal interaction terms. The last model (Model 9) incorporates the random temporal effect into Model 8, but obtains a slightly higher DIC (4089.78) and NLLK (2059.155). Therefore the best model is Model 8 which includes an unstructured spatial effect (u_i), a structured spatial component (v_i), a structured temporal random term (δ_t), and a space-time interaction random effect (φ_{it}).

Looking at the posterior estimates of the fixed effect predictors, the six models illustrate similar results. For example, economic deprivation is positively associated with police homicides in all the models, suggesting an elevated safety risk for police in more highly economically distressed areas. Also, residential stability is found to be negatively associated with the risk for police homicide in all six models. There are minor variations regarding the effects of female headed households, age structure, percent black, and incarceration rates in these models. However, when turning to the effect of the main exposure, there persists a non-significant effect of the discharge rates of the hospitalized mentally ill population on the police fatal victimization risk across all the models. This suggests that this exposure is not statistically associated with police homicides.

Considering the long time span the data covered, it might be helpful to inspect lattice (trellis) plots in separated time periods to detect whether temporal variations exist in the correlations between the outcome and the predictor. As shown in Figure 6.4, the discharge rates in the early years spread widely and showed weak positive correlations with the SMRs. In contrast, the discharge rates in the later periods varied in a much narrower interval (mainly near the zero point), and did not show an obvious positive relationship with the outcome. In some of these plots, the predictor and the outcome even

illustrated a negative correlation. Therefore, there may be some temporal heterogeneity in the association between the SMRs and the discharge rates of the inpatients. In other words, it is possible that the relationships between the fatal outcome and the release rates of the mentally ill hospitalized population varied over time.

Hence, based on Model 8, a new model, which incorporates a random walk temporal structure into the random slope of the discharge rates (Model 10), is fitted. The DIC (4088.05) and NLLK (2058.77) of Model 10 are slightly lower than that of other models, suggesting a further improvement in the model fit after taking the random temporal variation into account. Several other random slope models, i.e., an unstructured spatial effect, or a combination of unstructured and structured spatial effects, are also considered. However, these models yield higher comparison measures, indicating that incorporating spatial structures into the random slope is not necessary to improve the model fit. (The values of the comparison measures of these models are presented in Appendix B.) Since Model 10 fits the data best, this model is used in the subsequent analysis. Furthermore, an alternative temporal correlation structure, autoregressive correlation with order 1 (AR1), is applied in this model to evaluate whether this temporal correlation structure outperforms the random walk process. The model adopting AR1 produces higher DIC (4089.9) and NLLK (2059.3) values than the model using the random walk structure. Thus, the random walk temporal correlation structure is more appropriate for the analysis of this data.

The computation of the random temporal effect of the exposure is done by the linear combination feature of the INLA package, which combines the marginal effects from the

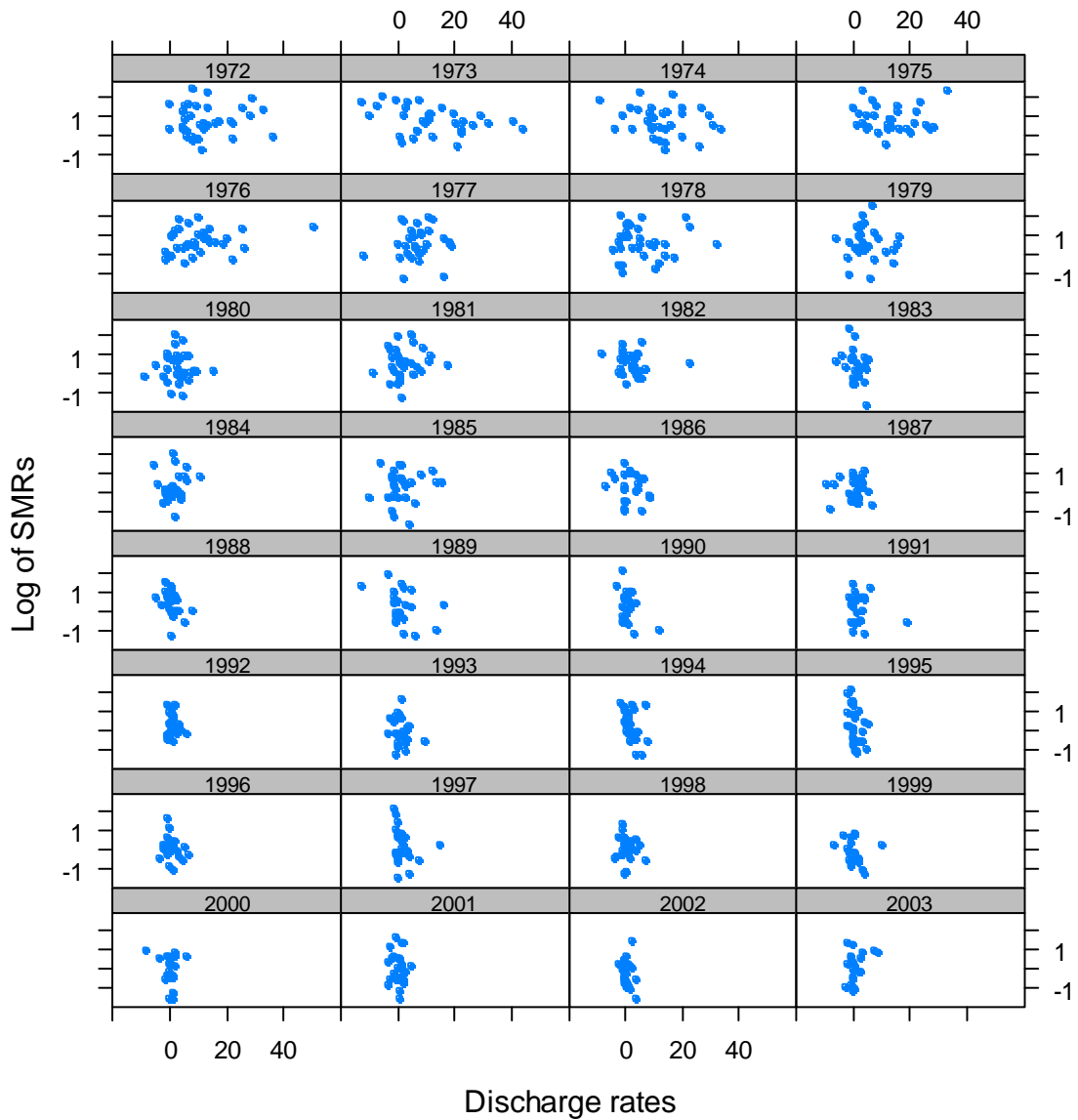


Figure 6. 4 Scatter plots of the log of SMRs against the discharge rates for each year (1972-2003).

Notes: There are some missing values of the log of the SMRs due to zero counts.

fixed part and random effect part.²² The temporal variation in the effect of the discharge rates on the police fatal victimization risk is illustrated in Figure 6.5. At the beginning of

²² The codes for the computation of the random temporal effect of the exposure are included in Appendix C.

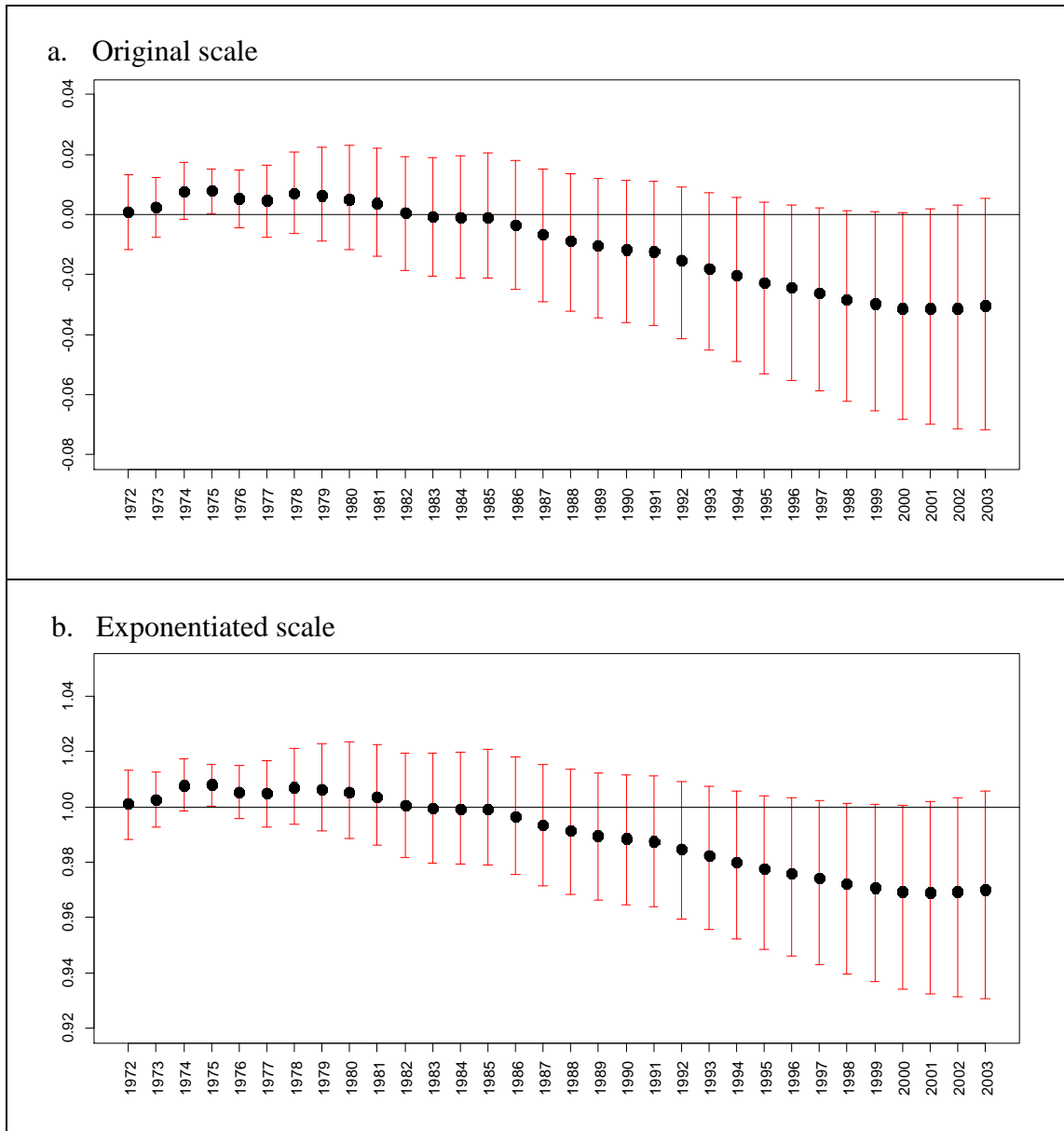


Figure 6.5 The temporal profile of the effects of the discharge rates of hospitalized mentally ill patients in the period 1972-2003

the 1970s, the estimated posterior means of the effect of the exposure showed an increasing pattern and became significantly positive in 1974. The positive effects remained stable for the next few years, but were not significant anymore. This result is consistent with the pattern observed from preliminary visual inspection. However, after the year 1978 or 1979, the effects of the discharge rates began to slide down, and

eventually became negative in the mid-1980s. This downward pattern of the effects of the exposure continued for the rest of the time periods, but with non-significant credible intervals.

Looking at the effects of other risk factors, percent of female headed household was significantly associated with homicides of police in a positive direction. Each one unit increase in percent of female headed household was associated with an 11 percent increase ($e^{0.1022} = 1.1076$) in the relative fatal risks of police homicides²³ (95% CrI 1.0460, 1.1707). Unexpectedly, the results show that age structure had a negative relationship with the SMRs of homicides of police. Each one percentage increase in the male residential population aged 15-34 is related to a 4.36 % decrease ($e^{-0.0445} = 0.9564$) in the estimated relative fatal risks for police (95% CrI 0.9399, 0.9562). This finding is contrary to the conventional wisdom that a high proportion of young males in the population increases the chances of police murders because it contributes to creating a criminogenic environment. As expected, the index of economic deprivation and percent black were positively associated with the risk of fatal victimization for police. The estimated mean effect size of economic deprivation was 0.1403 with a credible interval (0.0789, 0.1993), which translates to a 15.06% ($e^{0.1403} = 1.1506$) increase in the relative fatal risks for police for each one unit increase in economic deprivation index (95% CrI

²³ The estimated relative fatal risk can be viewed as estimated (smoothed) SMR. The raw SMR is calculated as observed death counts/ expected death counts, representing the relative risk of fatal outcome. In the spatio-temporal analysis, however, the raw SMR may be influenced by extreme values and space-time autocorrelations. Therefore, the raw SMR may not reflect the true risk (please see the discussion in Chapter Five). In contrast, using appropriate smoothed structures can yield a more accurate measure of the relative risk. When using explanatory variables to predict the relative risks, the interpretation would be the risk of an officer being killed in an exposed condition relative to the fatal risk of an officer in an unexposed condition.

1.0821, 1.2205). A one percent increase in the proportion of the population which is African American is found to be linked with a 1.54 % ($e^{0.0153} = 1.0154$) increase in police homicides risk (95% CrI 1.0018, 1.0286). Residential stability is found to have a negative effect on felonious killings of police, which is in the expected direction. The estimated exponentiated scale coefficient for a one percentage increase in residential mobility was 0.9572 with a 95% credible interval (0.9409, 0.9738). Likewise, the effect of incarceration rate residuals were negatively significant. Each one unit increase in the residual incarceration rate was associated with a 0.07% ($e^{-0.0007} = 0.9993$) decrease in police homicide risk (95% CrI 0.9987, 0.9999).

The regression is also conducted using the 2-year reporting period data (Model 11) and 4-year grouped data (Model 12) to explore the influence of using different aggregated level temporal units. The estimated parameters are displayed in Table 6.3. The results show that the analyses using biannual data and four-year data yield very similar results to that using annual data. These results suggest that the proposed analysis strategy is robust whether analyzing the data using annual, two-year, and four-year aggregated data. Also, the sensitivities of these models to overdispersion and excess zeros are almost the same. As shown in table 6.4, the negative binomial models or the ZINB models do not improve the fit of the model. Although the ZIP models provide slightly lower DIC and/or NLLK values across these three models, such improvements are essentially negligible. Furthermore, the effect estimations in the Poisson models and the ZIP models are very close. Therefore, the Poisson model is kept because it is more parsimonious. In the next section, to illustrate the spatial patterns of related effects

Table 6.3 Results for the random slope models using different reporting period data.

Parameters	Model 10 Annual data		Model 11 Two-year grouped data		Model 12 Four-year grouped data	
	mean	95% CrI	Mean	95% CrI	Mean	95% CrI
Intercept	3.1261**	1.6126, 4.5020	3.4514**	2.0753, 4.7258	3.5384**	2.2507, 4.8033
RELEASE RATE	-0.0097	-0.0240, 0.0040	-0.0023	-0.0114, 0.0065	0.0024	-0.0033, 0.0081
FEMALE HEADED	0.1022**	0.0450, 0.1576	0.1075**	0.0522, 0.1619	0.0861**	0.0256, 0.1478
POP DENSITY	-0.0005	-0.0010, 0.0001	-0.0005	-0.0010, 0.0000	-0.0004	-0.0010, 0.0001
STABILITY	-0.0437**	-0.0609, -0.0266	-0.0450**	-0.0621, -0.0279	-0.0479**	-0.0646, -0.0315
AGE STRUCTURE	-0.0445**	-0.0620, -0.0448	-0.0503**	-0.0663, -0.0333	-0.0440**	-0.0610, -0.0269
VIOLENT CRIME	0.0002	-0.0002, 0.0006	0.0002	-0.0002, 0.0006	0.0001	-0.0003, 0.0005
INCARCERATION	-0.0007**	-0.0013, -0.0001	-0.0008**	-0.0014, -0.0002	-0.0006**	-0.0012, -0.0001
ECO DEPRIVATION	0.1403**	0.0789, 0.1993	0.1388**	0.0792, 0.1958	0.1560**	0.0923, 0.2174
GINI	-1.3531	-3.6382, 1.0224	-1.5826	-3.6872, 0.6071	-1.6564	-3.7588, 0.4718
PERCENT BLACK	0.0153**	0.0018, 0.0282	0.0141**	0.0003, 0.0271	0.0151**	0.0012, 0.0282
Model fit						
DIC	4088.05		2654.47		1608.64	
pD	157.23		35.46		30.22	
NLLK	2058.774		1330.881		807.971	

Notes: ** - significant with 95% credible intervals that do not contain 0; * - marginal significant with 95% credible intervals that reach 0; coefficients are not exponentiated.

in a simpler manner, the Poisson model employing four-year reporting period data, which does not differ from the analysis using original annual data, is chosen.

Table 6.4 Comparison measures of fit for the Poisson, negative binomial, ZIP, and ZINB models.

		Annual data	Biannual data	Four-year data
Poisson	pD	157.23	35.46	33.22
	DIC	4088.05	2654.47	1608.64
	NLLK	2058.77	1330.88	807.97
NB	pD	33.36	30.35	26.87
	DIC	4114.82	2668.08	1638.01
	NLLK	2056.56	1332.51	816.51
ZIP	pD	139.35	87.18	33.32
	DIC	4094.50	2650.37	1607.78
	NLLK	2058.51	1329.975	807.08
ZINB	pD	33.54	31.41	27.15
	DIC	4116.35	2668.46	1638.41
	NLLK	2057.11	1332.17	816.43

6.2 SPATIO-TEMPORAL MAPPING

The estimated risks for each state across the time periods are presented in Figure 6.6. Compared to the raw SMRs of police murder mapped in Figure 5.2, the estimated risks reflect more stable temporal and spatial patterns. Also, these patterns can be more easily detected than using raw SMRs. It shows that the risk of officers being killed feloniously in the line of duty decreases over time in general. However, in each period, the states in the South had elevated fatal risks for police compared to other states, while the states in the northeast had the lowest estimated fatal risks on average. These patterns remained stable and did not suffer from the influence of extreme observations over time.

Although the map of the estimated risks is suggestive to reflect the spatio-temporal patterns of the fatal outcome, an “exceedance probability” (Richardson, Thomson, & Elliott, 2004) mapping method which takes the full advantage of Bayesian analysis can be more informative. An exceedance probability for an area is the probability that the

estimated posterior relative risk is greater than a specific value (i.e., 1.5, which means 1.5 times the average risk in the time period of interest). A high probability (i.e., 90%) of the estimated risk higher than this value indicates the “significance” of the local risk elevation. Mapping the exceedance probabilities can help identify the locations where unusually high risks exist. Such locations represent spatial clusters of high risk areas.²⁴ Therefore, mapping exceedance probabilities can be viewed as the Bayesian approach to detect hotspots.

Figure 6.7 displays the distributions of the probabilities that the estimated posterior fatal risks were greater than 1.5 times the average risks in each time period (which were categorized as larger than 60%, 80%, and 90%). This figure clearly illustrates that several southeastern states constituted a concentrated high-risk region for police safety. This spatial pattern persisted over the whole time span in question. The states of Georgia, Louisiana, Mississippi, and South Carolina were the core members of this group, while Arkansas, Tennessee, North Carolina, and Texas occasionally joined this group. Some western states, such as Arizona, Nevada, and New Mexico also became hot spots in some time periods. Among these states, Mississippi remained the most consistently dangerous state for law enforcement officers across the time periods.

Figure 6.8 shows the density plots of unstructured and structured spatial random effects. According to these plots, the unstructured spatial random effect term is approximately normally distributed as specified and expected. The structured spatial random effect is right skewed, reflecting differing patterns across low and high risk states. Mapping the unstructured spatial component and the CAR component (Figure 6.8) is helpful to appreciate such patterns.

²⁴ The exceedance probabilities are computed by employing the INLA function `inla.pmarginal()`.

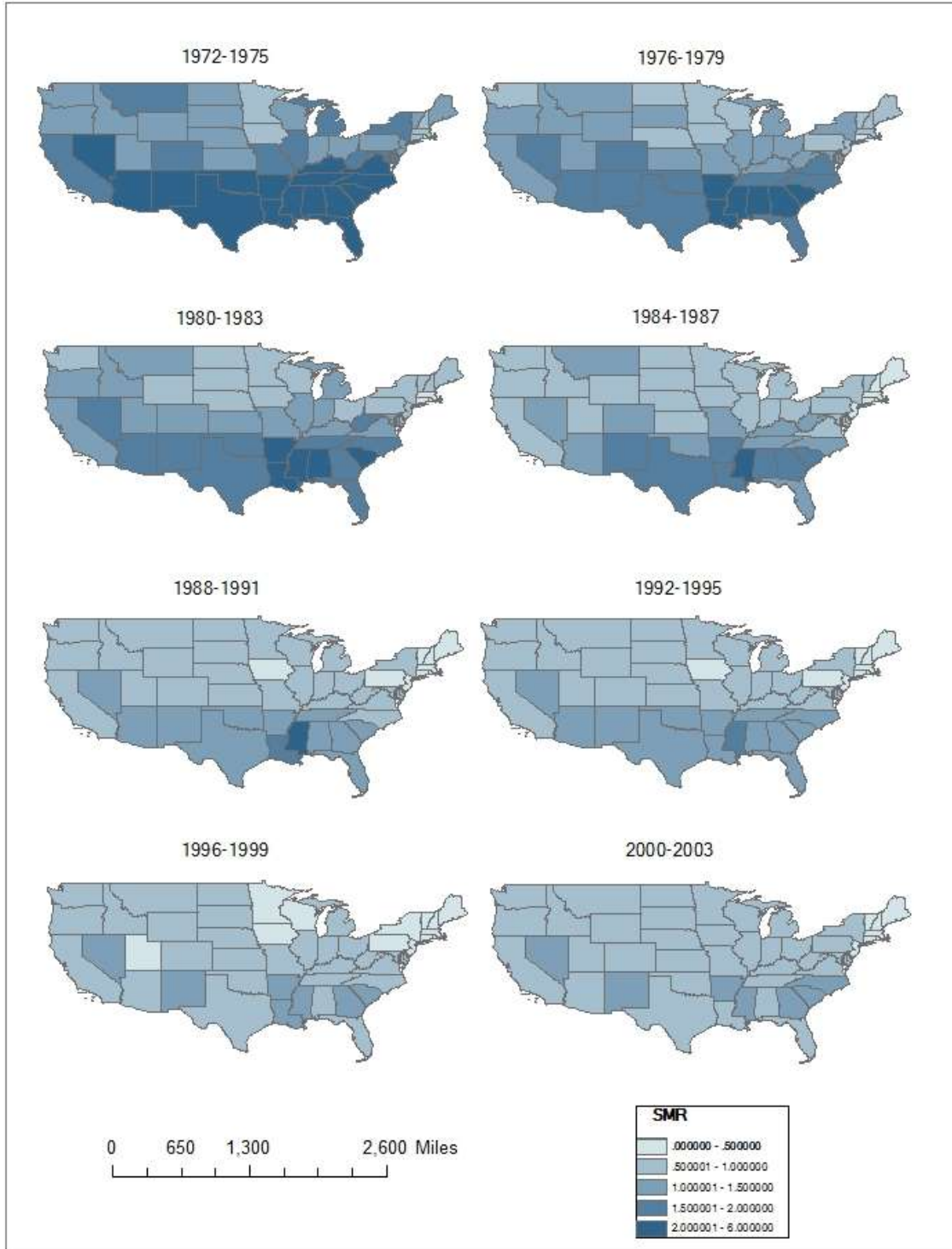


Figure 6.6 The map of the estimated posterior fatal risks in the period 1972-2003

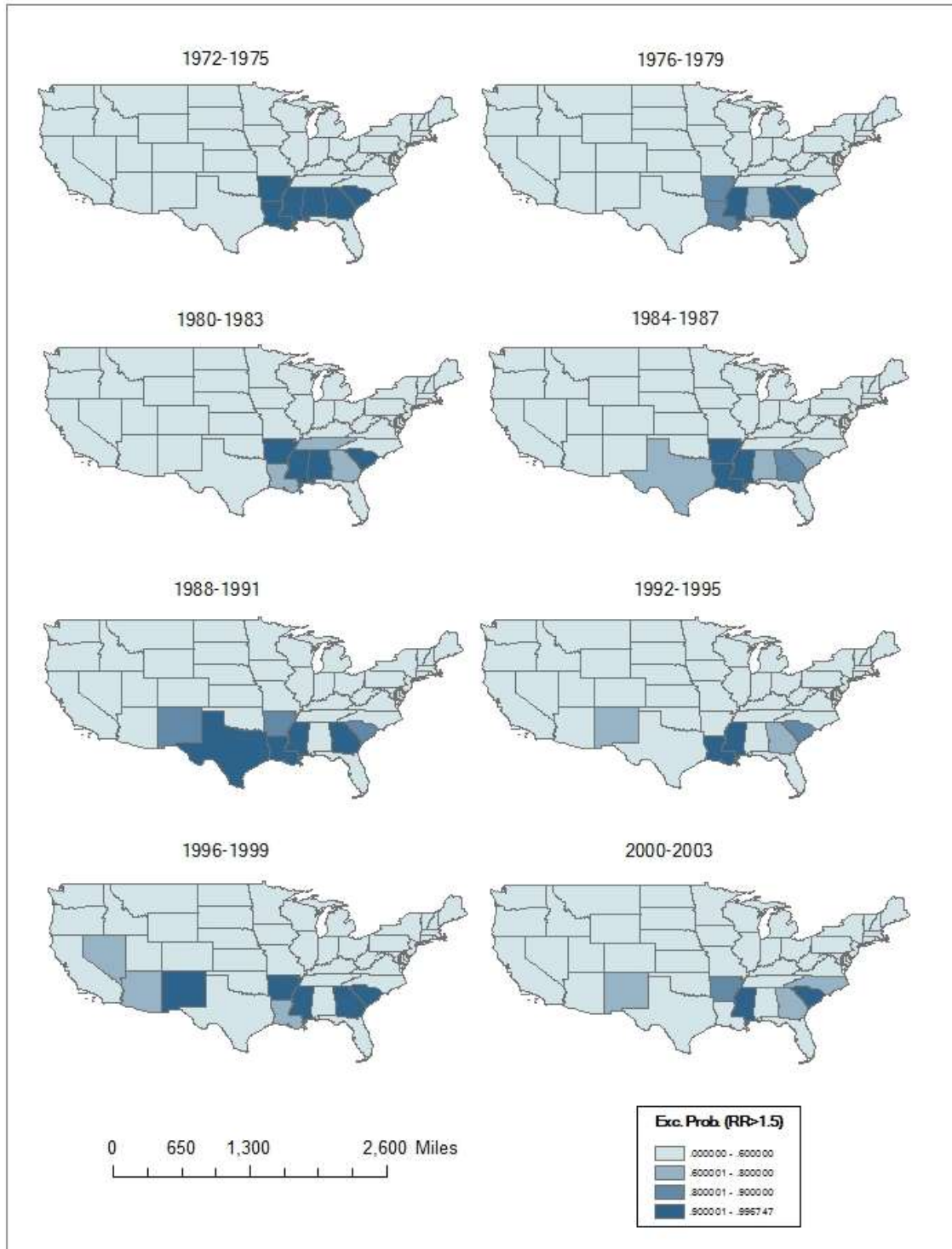


Figure 6.7 The distribution of the probabilities that the estimated posterior fatal risks were greater than 1.5 times the average risks in each time period from 1972 to 2003
Notes: The probabilities are categorized as larger than 60%, 80%, and 90%.

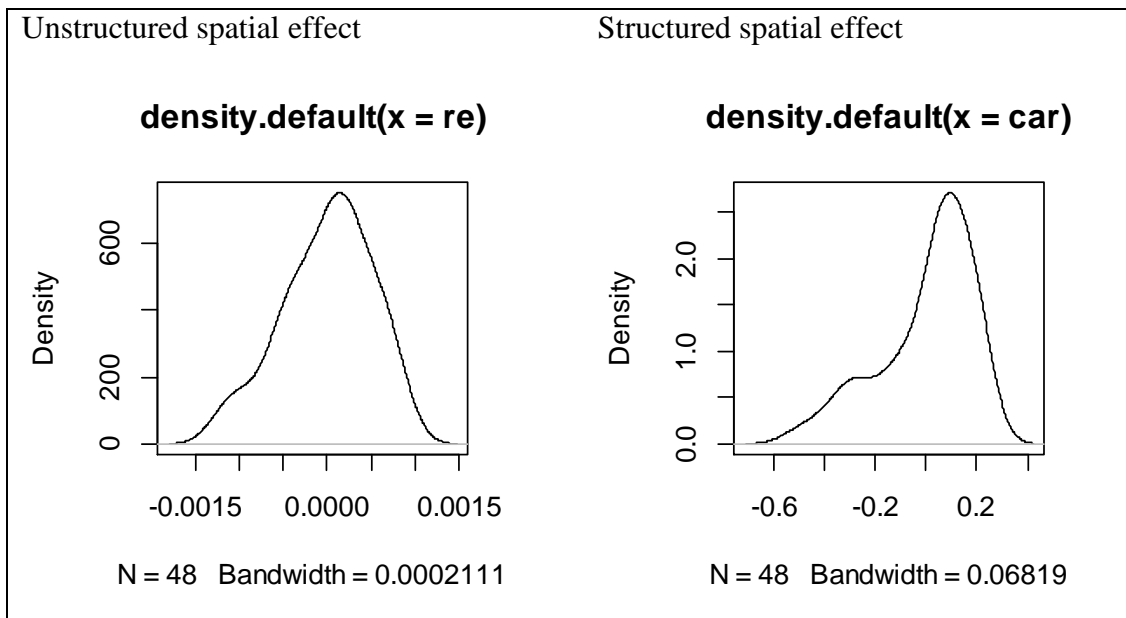


Figure 6.8 The density plots of unstructured and structured spatial random effects

As illustrated in Figure 6.9, the unstructured spatial random effects are distributed randomly across the country. In contrast, the structured spatial random (CAR) effect reveals that elevated risks existed in several southern states, western states, and many midwestern states, while the states on the west coast had decreased fatal risks for police. This structured spatial random effect represents the residual relative risk for each area (compared to the whole country) after all the covariates have been taken into account. Therefore, this figure suggests that there were still excess heightened fatal victimization risks for police in these areas even after controlling for all the predictors adopted in this analysis. As will be discussed in the next chapter, such excess risks could be the results of the similar unmeasured risk factors in these areas, and could be used to suggest directions for future research.

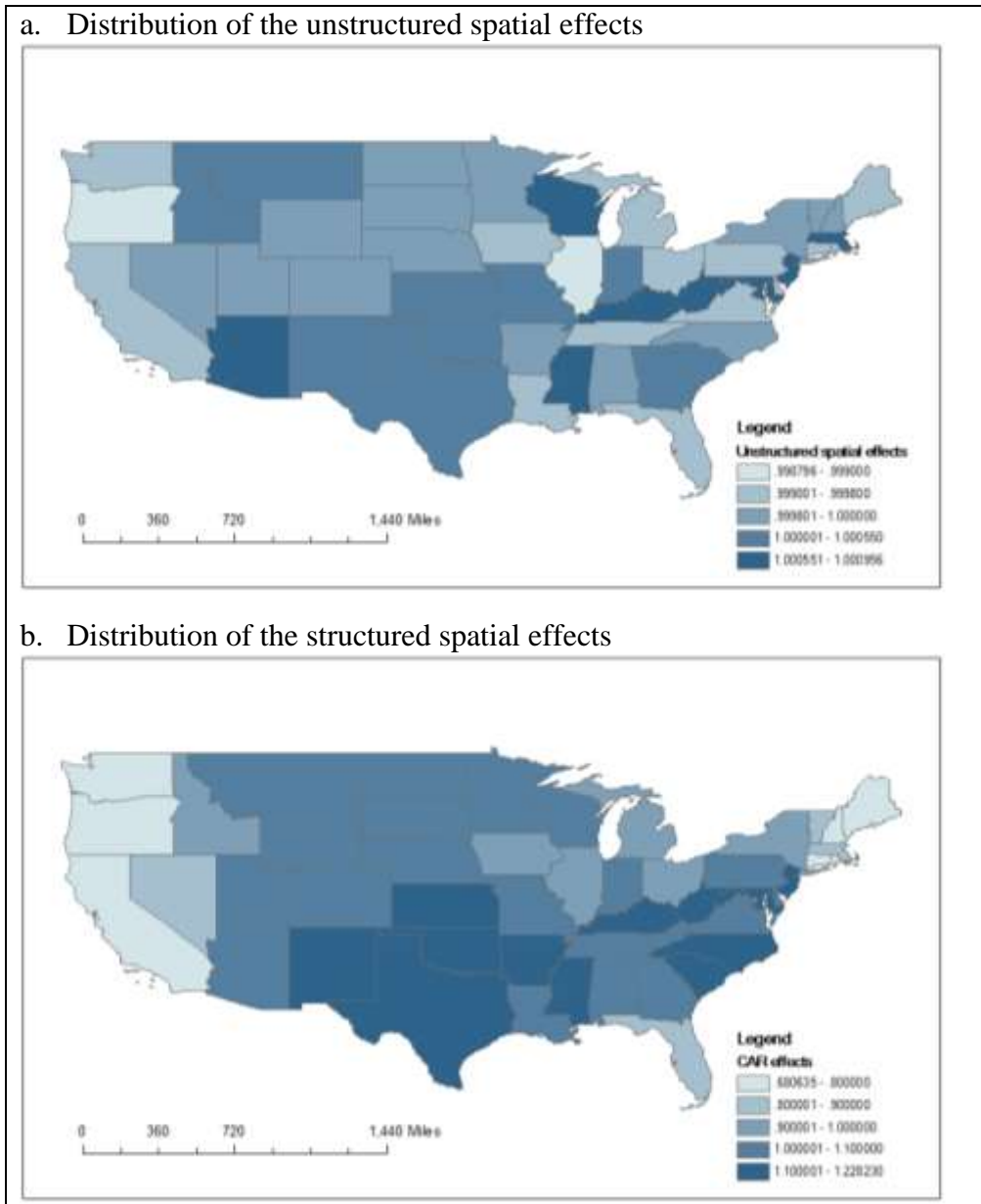


Figure 6.9 Distribution of the spatial random effects

The temporal effects are listed in Table 6.5 and also displayed in Figure 6.10. The upper panel of Figure 6.10 illustrates the effect size on the original scale, while the lower panel presents the effect size on the exponentiated scale. There appears to be no dramatic increase or decrease in the patterns, suggesting that the structured effect of time is relatively stable. The temporal effect showed a slight downward trend in general. The

coefficient on the exponential scale was above 1 at the beginning, but dropped down slightly and went under 1. However, the magnitudes of all the temporal effects were very small and not significant. This nearly flat pattern suggests that most of the temporal variations in the police homicide risks had been explained by the predictors included in the model (i.e., incarceration) and/or space-time interaction random effects.

Table 6.5 Temporal effects of the estimated SMRs

Year	1972-1975	1976-1979	1980-1983	1984-1987
Prob. > mean risk	0.5913	0.5976	0.5670	0.5196
Year	1988-1991	1992-1995	1996-1999	2000-2003
Prob. > mean risk	0.5085	0.4410	0.3845	0.3718

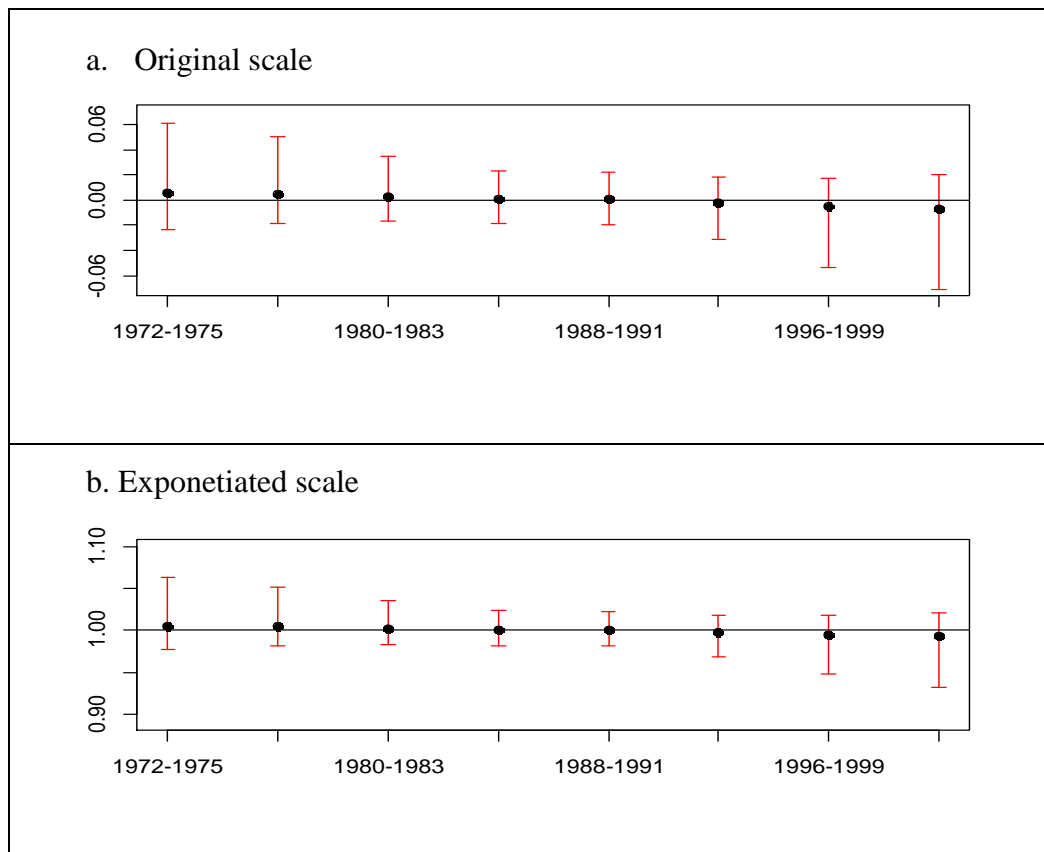


Figure 6.10 Graphic illustration of the temporal effects of the estimated SMRs

The space-time interaction effects can be viewed as the residual heterogeneity after the unstructured spatial effect, spatially structured effects, and structured temporal effects have been incorporated into the model. The fitted posterior risks from the interaction term can be extracted from the INLA model and mapped. The mapping of space-time interaction may reflect the variations in the estimated mortality risks due to some emerging or diminishing local risk factors (Richardson et al., 2004). If there are some clusters that exist over time, attention should be paid to investigate the possible reasons. Similar to the mapping of estimated fatal risks, the exceedance probabilities for the police homicides risks are mapped. Figure 6.11 displays the distribution of the exceedance probabilities from 1972 to 2003. There appear to be some random patterns of high risk states, but no persistent spatial clusters exist across time, suggesting that there were some local hazard factors for police fatal victimization that emerged in these states but did not last long. Locating these specific factors warrants further exploration.

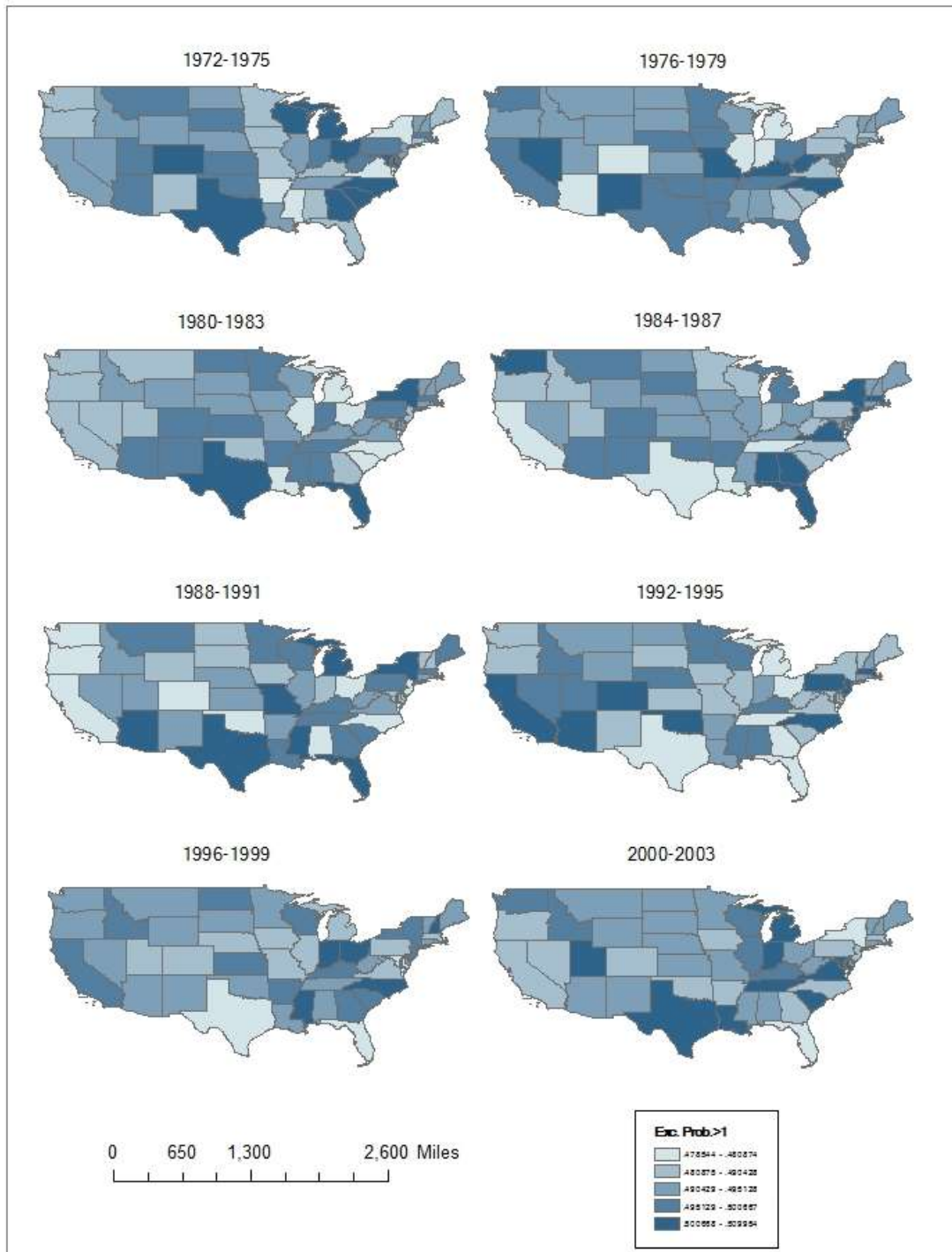


Figure 6.11 The maps of the exceedance probabilities ($RR > 1$) of the space-time interaction effects in the period 1972-2003

CHAPTER SEVEN DISCUSSION AND CONCLUSION

7.1 DISCUSSION OF RESULTS AND IMPLICATIONS

Researchers have observed that handling mentally ill individuals has become a regular part of a police officer's daily job since the deinstitutionalization movement started in the 1950s. Although there are widespread concerns about the elevated safety threats to law enforcement officers presented by mentally ill people, no published study has examined the relationship between victimization risks for police and the release of institutionalized mentally ill patients. This dissertation helps fill this gap by analyzing panel data for the years 1972-2003 to explore whether increases in the discharge rates of mental health patients living in state/county psychiatric hospitals are associated with murders of law enforcement officers. This study applies a Bayesian-based hierarchical spatio-temporal analysis approach to account for the spatio-temporal variations and autocorrelations. Also, a mapping strategy is employed to visually display the estimated risks of police murders and related spatial and temporal effects.

The releases of mentally ill patients and homicides of police

The results of the analysis show that the release rates of hospitalized mentally ill persons were not associated with the fatal victimization risks for police in general, after adjusting for the effect of violent crime rates, incarceration rates, economic deprivation, residential stability, percent black, Gini index, percent female headed household, population density, age structure, and economic deprivation. When a random slope model

is adopted, it is found that the relationship between the fatal outcome variable and the discharge rates of institutionalized mentally ill patients varied across time. Namely, the effects of the discharge rate of mentally ill persons on police homicides showed an increasing trend in the 1970s and became significantly positive only in 1974, but began to decrease afterward and became negative (non-significant) after the mid-1980s.

This finding suggests that the large number of released mentally ill people did not pose elevated fatal risks for police in the most of the time periods in question, which is in opposition to the findings depicted in prior perception research and descriptive reports. There are several possible reasons that could explain this discrepancy: First, the perceived elevated safety risks for police posed by the mentally ill population could actually be the effect of some social structural factors rather than the mentally ill population itself. This study finds that residential stability, percent black, female headed household, and economic deprivation had significant impacts on the safety risk for police (which will be discussed in detail later). Compared to the general population, persons with mental illnesses are usually more vulnerable to economic strains. When they experience unemployment or financial difficulty, they often lack the means to address these crises. Meanwhile, their disrupted families may hardly be able to provide necessary spiritual and material support to them. To cope with these stresses, many of them may resort to drugs or alcohol, which in turn cause a relapse of their mental disorders (Mechanic & Rochefort, 1990; Sheets, Prevost, & Reihman, 1982). Also, through a social disorganization perspective, the social capital and collective efficacy needed to monitor and help mentally ill individuals in need are low in areas with high residential mobility and racial heterogeneity. Hence, many mental health patients in such areas may not

receive necessary assistance and remain untreated. As a result, they might exhibit extra violent tendencies and constitute a safety threat to community and police. Therefore, releasing mentally ill people into communities was a much less important risk factor of police homicides in comparison with these socio-economic variables.

Second, police may have adapted to the deinstitutionalization movement and post-deinstitutionalization era and made necessary adjustments to face the challenges brought by the release of a large number of mentally ill individuals. The decreasing trend and the negative signs of the effect of the release rates of mentally ill patients in the second half of the period in question lends some support to this argument. The exact reason for this adaptive pattern is not yet clear. The mass incarceration which has occurred in recent decades may lead to the decrease in the number of mentally ill persons with deviant behaviors living in communities, thus offsetting the effect of releasing mentally health inpatients; however, this is unlikely the reason here because this study has considered the effect of residual incarceration rates. A more plausible reason is that police benefited from improved training and the spread of the specialized response programs (i.e., CIT), which made them better prepared to handle encounters involving mentally ill subjects than before. Therefore, the release of mentally ill inpatients was less of a major risk factor than previously. Whether or not this was the true reason for this temporal pattern, it is important that decision makers should continue their investment in the collaboration between law enforcement agencies and mental health service providers. Such collaboration is essential to help police obtain the necessary skills to cope with mentally ill individuals and improve the performance of specialized response programs, hence further reducing the safety risk for officers.

Last but not least, the fatal victimization risk only represents a fraction of safety risks for police. As discussed in Chapter Three, choosing police murders as the measure of threat may underestimate the safety risk for police. Many non-fatal shootings and other types of non-fatal assaults are also dangerous to officers. Missing these non-fatal incidents could have a potential negative influence on measurement validity. However, using fatality data is based on the limitations of the available data and the unavailability of certain incidents (e.g., nonfatal shootings of police). In the absence of data accurately recording these nonfatal assaults, it is impossible to obtain a more complete picture of the relationship between releasing mentally ill inpatients and police safety risks. Therefore, it is imperative to gather necessary information from non-fatal attacks on a broader scale and to use more consistent recording protocols. Policymakers need to think about improving the existing data collecting programs to encourage more local agencies to participate and provide reliable and valid data.

No matter what reason was truly responsible for the finding I discussed above, dispelling perceptions of the danger of persons with mental illness among police (at least in terms of a low risk for the officers of being murdered) is crucial for policing mentally ill populations. Unduly stressing the safety threat from mentally ill people may increase police's expectation to use force in encounters involving mentally ill persons, which could elevate the likelihood of using force in these encounters. For the same reason, while using force is unavoidable in some cases, the overstatement of the threat from mentally ill persons could drive police to exercise excessive force against them to subdue these "extremely dangerous" mentally ill subjects. These situations could increase the injury and death risks for both parties instead of reducing the risks. Furthermore, such a

perception could cause discrimination against and rejection of mentally ill persons. Officers influenced by this perception may treat mentally ill subjects with negative attitudes and tend to ignore their requests for service. Such response patterns might foster dissatisfaction and hostility from these mentally ill subjects toward police, which in turn increases the chances of police-citizen conflict.

It should be noted that inadequate treatment and the susceptibility to adverse socio-economic factors appear to be the fundamental reasons for the elevated propensity for violence among some persons with serious mental illnesses, not the mental illnesses themselves. To reduce deviant behaviors among mentally ill people, greater efforts should be made to provide more appropriate mental health services and to improve mentally ill people's socio-economic statuses rather than segregating them from the public. Of course, this is beyond the responsibility of the criminal justice system, and requires a reform of mental health and welfare frameworks. For law enforcement, the practical implication is to educate field officers to understand the relationship between violence and mental illness, train them to identify mentally ill subjects and assess those subjects' needs in a timely manner, as well as provide special assistance resources if necessary.

Other important risk factors for murders of police

Turning to other important risk factors, one of the significant findings of this analysis is the positive effect of resource deprivation on police killings, and it is concluded that police were more likely to be murdered in states with low income levels, high poverty rates, and high unemployment rates. This result is congruent with some prior studies (Batton & Wilson, 2006; Chamlin, 1989; Kaminski, 2002; Kaminski & Marvell, 2002,

Kaminski, 2008). According to a social control perspective, economic deprivation diminishes local communities' ability to form effective social networks and resources, thus reducing formal and informal controls (Sampson et al., 1999; Sampson & Raudenbush, 1999). From the point of view of strain theory, resource deprivation produces frustrations and hostility to society (Merton, 1938; Taylor et al., 1973). Either way, economic deprivation fosters a criminogenic environment, which increases the proximity of police to motivated offenders and potential attacks. Identifying the exact pathway from adverse economic conditions to crime-promoting environments is beyond the scope of this dissertation, but this study provides strong support for the effect of economic disadvantage on police murders.

As expected, several other factors reflecting social disorganization are also found to be related to police homicide. The findings show that residential stability was negatively associated with police homicides, while female headed household and percent black were positively linked to felonious killings of officers. Low residential stability, high family disruption, and high racial heterogeneity make it difficult for a community to form stable social connections, reach consensus, and make efforts to solve existing problems, thus reducing social capitals and informal social controls (Parker, McCall, & Land, 1999; Sampson & Groves, 1989; Sampson & Laub, 1993; 2005). Therefore, these factors may have elevated the potential for crime and delinquency, which in turn increased the exposure and proximity of officers to motivated offenders, thus posing a heightened risk for police. This study yields some evidence to the effect of these factors on the fatal risks for police, hence lending support to the social disorganization perspective in explaining police homicides.

This study also finds that a high percentage of males aged 15-34 is negatively significantly associated with the risk for police of being murdered. Since prior studies found that a high proportion of young males was linked to elevated general crime levels (Hirschi & Gottfredson, 1983; Messner & Rosenfeld, 1999:36), this variable was previously assumed to be positively related to the chances of police murders because it contributes to creating a large pool of motivated potential offenders. However, most of the existing studies reported non-significant effects of the age structure variable (Bailey & Peterson, 1994; Fridell & Pate, 1995; Kaminski & Marvell, 2002). The present study even finds a negative effect of a high proportion of young males on police homicides. These results imply that the role of age structure in the risks for police homicides may differ from that in general homicides.

Another finding of this study is the negative association between incarceration rates and police homicides. This finding is consistent with the findings in some extant studies (Batton & Wilson, 2006; Kaminski & Marvell, 2002). Thus this study adds some support to the negative effect of incarceration on the fatal risks for police. However, the effect size of incarceration is very small: a 0.07 % decrease in police homicide risks corresponds to each one unit increase in the residual incarceration rate. The mass imprisonment in recent decades could be a double-edged sword to the safety of police. On the one hand, incarceration may shrink the population of active offenders or deter potential offenders, but on the other hand, it is correlated with aggressive policing. Aggressive policing may have an adverse influence on the risk for police killings via greater arrests, which has been shown to be a risk factor (Kaminski, 2002, 2004). The

process in which mass incarceration has influenced murders of police deserves further exploration.

This study does not find an effect of residual violent crime levels. This factor is assumed to be related to the proximity of officers to motivated offenders, thus would be expected to have impacts on felonious killings of officers. However, several prior studies reported a null or even a negative effect of violent crimes (Bailey & Peterson, 1987; Peterson & Bailey, 1988; Chamlin, 1989). The present study stands in line with those prior studies and lends some support to the null effect of this regressor. Additionally, this paper does not find significant effects of population density and Gini index, which are used to represent social disorganization and relative economic strains (Shaw & McKay, 1969; Crosby, 1976). Some previous studies also examined the effect of these regressors, but did not report consistent results (Bailey & Peterson, 1987; Bailey & Peterson, 1994; Chamlin, 1989; Fridell & Pate, 1995; Kaminski & Marvell, 2002). The effect of these factors needs to be evaluated by further research.

Utility of spatio-temporal mapping

This study illustrates the trend patterns of the risk for police of being murdered and its associations with the changes in the institutionalized mentally ill population and other important predictors over time and across states. The advantage of a Bayesian based spatial-temporal analysis is illustrated by this analysis: It not only helps us accurately estimate the risks of outcome incidents and depict the clear relationship between the response variable and related risk factors, but also discerns certain patterns from residuals due to unmeasured or unobservable covariates.

An exceedance probability mapping of the estimated fatal risks identifies a high-risk hot spot for police safety which consists of several southeastern states. The states of Alabama, Georgia, Louisiana, Mississippi, and South Carolina consistently appeared in this hot spot across time. This finding lends strong support for the early findings that fatal victimization risks for police were higher in the southern states (Bailey & Peterson, 1987; Kaminski, 2008; Kaminski et al., 2000). When regional difference was examined in the traditional regression models, a general geographic attribute (i.e., South) was assigned to each area, and the significance of this geographic indicator was tested. However, such an approach may not work well if there is considerable heterogeneity in the same geographic region. For instance, although Florida is located in the South, it behaved quite differently from its neighbors by exhibiting low or average fatal risks for police most of the time. Such deviations could distort the test result of the variable “South”. This may be a possible reason why prior research had mixed findings about the effect of region difference on the police murders (Fridell & Pate, 1995; Peterson & Bailey, 1988). In contrast, the mapping method used in this study produces visualized and probability-based risk estimates for each area, and is therefore much more powerful and efficient (Lawson, 2003). In addition, the exceedance probability provides a more intuitive way to interpret the estimated risks (Richardson et al., 2004).

The map of the structured spatial random (CAR) effects reveals that elevated residual risks existed in several southern states, southwestern states, and many western states, while the states on the west coast had decreased residual fatal risks for police after controlling for the effect of all the predictors adopted in this analysis. Such excess risks could result from similar unmeasured risk factors in these areas, and could be used to

suggest a direction for future research. The specific reason for such a spatial pattern warrants further investigation. As mentioned in Chapter Four, a southern subculture theory, which argues that southerners are more likely to respond aggressively to interpersonal challenges, has been used to explain the elevated murder risks for police in the South (Wolfgang & Ferracuti, 1982:215). However, the spatial pattern shown in Figure 6.6 implies that many western states and southwestern states may share certain common social-environmental traits with the southern states, thus reflecting similar excess risks. In this case, firearm availability in these states, for instance, may be a more plausible contributor. Further research could focus on the effect of firearm accessibility on police homicides in these areas.

Prior research found that the early 1970s was the peak period of the number of police murdered nationally, and that the counts decreased dramatically thereafter (Kaminski & Marvell, 2002). The present study observes a consistent temporal pattern in terms of SMRs, suggesting that there was a substantial decline in risks over time. However, the structured temporal effects on the risks of police homicides only showed a slight downward trend, and the magnitudes of these effects were small and non-significant. This result implies that the proposed model has included predictors which can explain most of the temporal variations in the police homicide risks between 1972-2003. The increased incarceration rates and the decreased violent crime levels could be responsible for this trend, but other variables might also play roles in such changes. In any case, after controlling for these predictors, no national-level historical changes, such as the war on drugs (which may have been represented by the increased incarceration rates), had detectable impacts on the fatal risk for police during the period in question.

Although the maps of the space-time interaction effects do not show specific patterns across space and time, the distribution of the high-risk areas is worth further examination. The space-time interaction effects represent the residual heterogeneity after the unstructured spatial effect, spatially structured effects, and structured temporal effects have been considered in the model. Therefore, some state-level historical changes, i.e., the implementation of a three-strike law, may impact the risk in this state at a specific time point. A close look at these high-risk states may reveal the connection between the heightened risk for police and certain emerging risk factors.

To summarize, the results of the analysis indicate that the change in the hospitalized mentally ill population had no statistically significant effect on the fatal victimization risk for police in general, but showed some temporal variations when a random slope model was employed. Meanwhile, this study provides support for the negative effects of residential stability and residual incarceration rates, and support for the positive effects of economic deprivation, female headed households, and percent black, but reveals a negative effect of age structure. A hot spot of high-risk areas for police consisting of Georgia, Louisiana, Mississippi, and South Carolina is identified by exceedance probability mapping of the estimated SMRs. Elevated residual risks for police due to unmeasured risk factors are found in several southern states, western states, and midwestern states.

7.2 LIMITATIONS AND FUTURE DIRECTIONS

This study examines the influence of deinstitutionalization on the safety of the police, and provides a visualized representation of the fatal victimization risk for police. However, it is not free of limitations. The weakness of choosing police murders as the

measure of threat has been discussed, and there are some other limitations that need to be pointed out.

First, due to its ecological nature, this study can only provide a general picture of the trends and patterns of the impact of deinstitutionalization on the occupational risk for officers and identify state-level risk factors. The findings cannot be used to improve the understanding of police contacts with mentally ill people at the incident or individual-level. Further research on the incident/individual-level is warranted to obtain a more comprehensive picture of interactions in encounters involving persons with mental illness. Such studies would require reliable information about the subject's mental status, the officer's disposition, and related contextual factors in police-citizen contacts, which is usually unavailable. Therefore there is a distinct need to encourage practitioners to collect such information with dependable recording protocols.

Second, the weakness of secondary research may impact the findings of this study. Although the measures used in the present study are mainly from official government sources, they are not immune from measurement error and encoding mistakes. Also, considering the long time span in this study, the changes in the operational definitions and procedures used by the organizations to collect data over time may affect the consistency and the quality of the data. Hence, the measurement validity and the internal validity of the present study may be influenced by the quality of the original data.

Next, this study examines the relationship between the fatal victimization risk for police and the changes in the amount of hospitalized mentally ill persons at the state-level. However, states are relatively large spatial units. There still are considerable heterogeneities in policing models, response programs, and available resources within

each state. The effect of these factors cannot be captured explicitly by this study using state-level aggregated data. Also, the analysis of this relationship in relatively small geographic areas could benefit more from Bayesian hierarchical spatial modelling, because the effect of spatial dependence is more prominent when smaller spatial units are used. Further study using smaller spatial units, such as counties, cities, or agencies, would be worth conducting to identify the effect of more local policy factors.

Finally, a common assumption used in the existing research is that the effects of risk factors are fixed over time and space. Such an assumption may be too restrictive in many cases. As illustrated in this paper, the relationship between the risks for police of being murdered and the changes in the institutionalized mentally ill population varied temporally. Given the highly increased complexity in the model, this analysis only focuses on the random temporal effects of the discharge rates, which is the main exposure. However, it is possible that the associations between fatal outcomes and other important predictors varied across space and/or time in the same manner. Such varying associations may come from some unmeasured local eco-social structures or temporary events. Therefore, a more flexible model which can accommodate the spatially and/or temporally varied effects of the predictors could be developed in further research.

Despite these limitations, this study examines a previously unanswered research question regarding the large number of hospitalized mentally ill patients released through the deinstitutionalization movement on the safety risk for police. The findings increase our understanding of the impact of deinstitutionalization on the criminal justice system, and provide a more comprehensive picture about the factors associated with law enforcement officer homicide victimization. In addition, this study demonstrates the

utility of the Bayesian hierarchical spatio-temporal approach when analyzing crime data involving space and time information. Although this study does not answer all the questions about the spatial and temporal patterns illustrated in the analysis, it sets a stage for future research to conduct further exploration.

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APPENDIX A THE COLLINEARITY TESTS AND CORRELATION MATRICES OF ALL
REGRESSORS FOR SELECTED TIME PERIODS

Table A.1 VIFs and tolerances of all regressors in 1972-1975 data

Variables	VIF	Tolerance
DIFF	1.15	0.8696
RESMOBILITY	3.59	0.7115
BLACKPCT	2.32	0.4318
FEMALEHEADED	2.88	0.3475
POPDENSITY	1.92	0.5207
AGESTRUT	1.84	0.5430
CRIME	1.13	0.8882
ECODEPRIVATION	2.01	0.4987
GINI	1.89	0.5291
INCARC	1.11	0.9014
Mean VIF	1.76	

Table A.2 Eigenvalues and condition indices for 1972-1975 data

Dimension	Eigenvalue	Condition Index
1	5.9767	1.0000
2	1.3704	2.0883
3	1.1740	2.2563
4	0.9631	2.4911
5	0.6887	2.9459
6	0.4918	3.4861
7	0.2922	4.5222
8	0.0233	16.0169
9	0.0121	22.1898
10	0.0068	29.7308
11	0.0009	81.3978
Condition Number	81.3977	

Table A.3 Condition indexes and Variance-decomposition proportions, 1972-1975 data

Condition number using scaled variables = 81.40													
	CI	_cons	RESMOBI	BLACKPCT	FEMALEHEADED	POPDENSITY	AGESTRUT	GINI	INCARresid	CRIMEresid	ECODEPn	DIFFR2	
1	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
2	2.09	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.22	0.24	0.08	0.02	
3	2.26	0.00	0.00	0.01	0.00	0.05	0.00	0.00	0.14	0.05	0.22	0.02	
4	2.49	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.00	0.78	
5	2.95	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.64	0.58	0.00	0.05	
6	3.49	0.00	0.00	0.11	0.00	0.34	0.00	0.00	0.00	0.01	0.07	0.00	
7	4.52	0.00	0.00	0.41	0.00	0.25	0.00	0.00	0.00	0.02	0.31	0.01	
8	16.02	0.00	0.10	0.04	0.29	0.01	0.06	0.02	0.10	0.00	0.08	0.02	
9	22.19	0.00	0.07	0.10	0.25	0.01	0.34	0.07	0.07	0.00	0.04	0.07	
10	29.73	0.01	0.64	0.09	0.40	0.28	0.17	0.09	0.64	0.00	0.10	0.01	
11	81.40	0.99	0.19	0.24	0.06	0.04	0.43	0.82	0.19	0.00	0.09	0.01	

Table A.4 Correlation matrix of all regressors for 1972-1975 data

	DIFF	RESMOB~Y	BLACKPCT	FEMALE~D	POPDEN~Y	AGESTRUT	CRIME	ECODEP~N	GINI	INCARC
DIFF	1.0000									
RESMOBILITY	0.5563	1.0000								
BLACKPCT	0.1878	0.1663	1.0000							
FEMALEHEADED	0.1973	0.0841	0.7690	1.0000						
POPDENSITY	0.2109	0.4757	0.0570	0.3371	1.0000					
AGESTRUT	-0.2926	-0.4960	0.0433	0.1115	-0.2742	1.0000				
CRIME	-0.0296	-0.1787	0.4834	0.7462	0.2361	0.0426	1.0000			
ECODEPRIVA~N	0.0124	-0.0155	-0.2821	0.0203	0.5165	0.1196	0.2960	1.0000		
GINI	0.1258	0.2648	0.4183	0.3323	-0.0176	-0.1038	0.1545	-0.4775	1.0000	
INCARC	-0.1255	-0.3421	0.6755	0.5962	-0.1338	0.2679	0.5705	-0.1579	0.2744	1.0000

Table A.5 Correlation matrix of all regressors for 1976-1979 data

	DIFF	RESMOB~Y	BLACKPCT	FEMALE~D	POPDEN~Y	AGESTRUT	CRIME	ECODEP~N	GINI	INCARC
DIFF	1.0000									
RESMOBILITY	0.4499	1.0000								
BLACKPCT	0.0761	0.2883	1.0000							
FEMALEHEADED	0.3005	0.4198	0.8027	1.0000						
POPDENSITY	0.4915	0.5298	0.0818	0.4462	1.0000					
AGESTRUT	-0.2084	-0.5123	-0.0610	-0.1133	-0.3012	1.0000				
CRIME	-0.0271	-0.1212	0.4468	0.6477	0.2337	0.0267	1.0000			
ECODEPRIVA~N	0.0501	-0.0754	-0.2407	-0.0131	0.4524	0.2628	0.2893	1.0000		
GINI	-0.0309	0.1368	0.5816	0.4075	-0.1744	-0.1486	0.1506	-0.6820	1.0000	
INCARC	-0.1562	-0.2239	0.6763	0.5315	-0.1470	0.1324	0.6065	-0.1160	0.3914	1.0000

Table A.6 Correlation matrix of all regressors for 1980-1983 data

	DIFF	RESMOB~Y	BLACKPCT	FEMALE~D	POPDEN~Y	AGESTRUT	CRIME	ECODEP~N	GINI	INCARC
DIFF	1.0000									
RESMOBILITY	0.3791	1.0000								
BLACKPCT	0.0458	0.3348	1.0000							
FEMALEHEADED	0.1883	0.5054	0.8233	1.0000						
POPDENSITY	0.3602	0.5308	0.1030	0.4546	1.0000					
AGESTRUT	-0.1322	-0.4665	-0.0365	-0.0834	-0.2422	1.0000				
CRIME	0.0134	-0.0618	0.4279	0.6060	0.3201	0.0219	1.0000			
ECODEPRIVA~N	0.0073	-0.0793	-0.1837	0.0007	0.4786	0.3263	0.3399	1.0000		
GINI	-0.0200	0.0268	0.5642	0.3784	-0.2181	-0.1424	0.1771	-0.6320	1.0000	
INCARC	-0.0825	-0.1800	0.7305	0.5478	-0.1116	0.0806	0.5717	-0.1025	0.4494	1.0000

Table A.7 Correlation matrix of all regressors for 1988-1991 data

	DIFF	RESMOB~Y	BLACKPCT	FEMALE~D	POPDEN~Y	AGESTRUT	CRIME	ECODEP~N	GINI	INCARC
DIFF	1.0000									
RESMOBILITY	0.4728	1.0000								
BLACKPCT	-0.0559	0.2127	1.0000							
FEMALEHEADED	0.0272	0.1349	0.8211	1.0000						
POPDENSITY	0.3413	0.3521	0.1342	0.0725	1.0000					
AGESTRUT	0.0096	-0.1670	0.3586	0.4141	0.2349	1.0000				
CRIME	0.0728	-0.1362	0.5445	0.5782	0.2827	0.3174	1.0000			
ECODEPRIVA~N	0.2037	-0.0875	-0.0484	-0.1194	0.6788	0.4811	0.2637	1.0000		
GINI	-0.1910	-0.1452	0.4658	0.4810	-0.0621	0.0977	0.5061	-0.2473	1.0000	
INCARC	-0.1543	-0.2848	0.6849	0.6502	0.0023	0.2487	0.6654	-0.0144	0.4985	1.0000

Table A.8 Correlation matrix of all regressors for 2000-2003 data

	DIFF	RESMOB~Y	BLACKPCT	FEMALE~D	POPDEN~Y	AGESTRUT	CRIME	ECODEP~N	GINI	INCARC
DIFF	1.0000									
RESMOBILITY	-0.0530	1.0000								
BLACKPCT	0.4062	0.1709	1.0000							
FEMALEHEADED	0.3443	0.1211	0.8533	1.0000						
POPDENSITY	0.0049	0.3547	0.1734	0.1644	1.0000					
AGESTRUT	0.0518	-0.4386	0.1590	0.1862	-0.2724	1.0000				
CRIME	0.3813	-0.1773	0.5782	0.6174	0.1625	0.1113	1.0000			
ECODEPRIVA~N	-0.0579	-0.0858	-0.0871	-0.2075	0.5833	-0.0270	0.0056	1.0000		
GINI	0.0748	-0.0433	0.4859	0.6326	0.0984	0.1330	0.5710	-0.2032	1.0000	
INCARC	0.2683	-0.2445	0.6665	0.6942	-0.1668	0.2888	0.5362	-0.2985	0.6236	1.0000

APPENDIX B MODEL COMPARISON MEASURES FOR THE RANDOM SLOPE MODEL
(MODEL 10) USING DIFFERENT COMBINATIONS OF SPATIAL/TEMPORAL
STRUCTURES

Table B.1 Model comparison measures for the random slope model (Model 10) using different combinations of spatial/temporal structures.

	Random walk process	Random walk +unstructured spatial structure	Random walk +unstructured spatial structure +CAR
pD	157.23	159.18	159.41
DIC	4088.05	4090.33	4090.92
NLLK	2058.77	2066.225	2075.033

APPENDIX C THE MAIN CODES USED FOR THE REGRESSION

```
library(INLA)
#Non Parametric model beta + usii + csii + deltat + gammat + phit
#usii (unstructured spatial random effect) is modelled through iid
#csii (structured spatial random effect) is modelled through besag
#deltat (structured temporal random effect) is modelled as RW1
#gammat (unstructured temporal random effect) is modelled as iid
#phij (space-time random effect) is modelled as iid

#bivariate regression
#crosssectional, Model 1
formula.st<- OBSERVED ~ 1 +DIFFR2

#only structured temporal term (deltat), Model 2
formula.st<- OBSERVED ~ 1 + f(ID.year,model="rw1")+DIFFR2

#add the time variable as a linear predictor, Model 3
formula.st<- OBSERVED ~ 1 +DIFFR2+Year1

#only structured temporal term (deltat) with all predictors, Model4
formula.st<- OBSERVED ~ 1 + f(ID.year,model="rw1")+DIFFR2+ FEMALEHD
+ PDENSITY + RESM + AGESTRUT + CRIME + INCARC + ECO + GN + BLACK

#deltat+usii with all predictors, Model 5
formula.st<- OBSERVED ~ 1 + f(ID.year,model="rw1") +
f(ID.area1,model="iid")+DIFFR2+ FEMALEHD + PDENSITY + RESM + AGESTRUT
+ CRIME + INCARC + ECO + GN + BLACK

#deltat+usii+csii, Model 6
formula.st<- OBSERVED ~ 1 +f(ID.area,model="besag",graph="nc.adj") +
f(ID.year,model="rw1") + f(ID.area1,model="iid") +DIFFR2+ FEMALEHD +
PDENSITY + RESM + AGESTRUT + CRIME + INCARC + ECO + GN + BLACK
```

#deltat+usii+csii+phiit, Model 8

```
formula.st<- OBSERVED ~ 1 +f(ID.area.year,model="iid")
+f(ID.area,model="besag",graph="nc.adj") + f(ID.year,model="rw1") +
f(ID.area1,model="iid") +DIFFR2+ FEMALEHD + PDENSITY + RESM +
AGESTRUT + CRIME + INCARC + ECO + GN + BLACK
```

#deltat+usii+csii+gammat+phiit, Model 9

```
formula.st<- OBSERVED ~ 1 +f(ID.year1,model="iid")+f(ID.area.year,model="iid")
+f(ID.area,model="besag",graph="nc.adj") + f(ID.year,model="rw1") +
f(ID.area1,model="iid") +DIFFR2+ FEMALEHD + PDENSITY + RESM +
AGESTRUT + CRIME + INCARC + ECO + GN + BLACK
```

```
model.inla.st <- inla(formula.st,family="poisson",data=data,E=EXPECTED,
control.predictor=list(compute=TRUE), control.compute=list(dic=TRUE,cpo=TRUE))
model.inla.st <- inla(formula.st,family="nbinomial",data=data,E=EXPECTED,
control.predictor=list(compute=TRUE), control.compute=list(dic=TRUE,cpo=TRUE))
model.inla.st <- inla(formula.st,family="zeroinflatedpoisson1",data=data,E=EXPECTED,
control.predictor=list(compute=TRUE), control.compute=list(dic=TRUE,cpo=TRUE))
model.inla.st <-
inla(formula.st,family="zeroinflatednbinomial1",data=data,E=EXPECTED,
control.predictor=list(compute=TRUE), control.compute=list(dic=TRUE,cpo=TRUE))
```

#random slope model based on Model 8

#only a temporal structurer is included (RW1) , Model 10

```
formula.st<- OBSERVED ~ 1 + f(ID.year1,DIFFR2,
model="rw1")+f(ID.area.year,model="iid") +f(ID.area,model="besag",graph="nc.adj") +
f(ID.year,model="rw1") + f(ID.area1,model="iid") +DIFFR2+ FEMALEHD +
PDENSITY + RESM + AGESTRUT + CRIME + INCARC + ECO + GN + BLACK
```

#a temporal structurer and an unstructured spatial random effect are included (RW1+iid)

```
formula.st<- OBSERVED ~ 1 +f(ID.area2,DIFFR2,model="iid") + f(ID.year1,DIFFR2,
model="rw1")+f(ID.area.year,model="iid") +f(ID.area,model="besag",graph="nc.adj") +
f(ID.year,model="rw1") + f(ID.area1,model="iid") +DIFFR2+ FEMALEHD +
PDENSITY + RESM + AGESTRUT + CRIME + INCARC + ECO + GN + BLACK
```

#a temporal structurer, an unstructured spatial random effect, and a structured spatial random effect are included (RW1+iid+CAR)

```
formula.st<- OBSERVED ~ 1 +f(ID.area3,DIFFR2,model="besag",graph="nc.adj")+
f(ID.area2,DIFFR2,model="iid") + f(ID.year1,DIFFR2,
```



```

model="rw1")+f(ID.area.year,model="iid") +f(ID.area,model="besag",graph="nc.adj") +
f(ID.year,model="rw1") + f(ID.area1,model="iid") +DIFFR2+ FEMALEHD +
PDENSITY + RESM + AGESTRUT + CRIME + INCARC + ECO + GN + BLACK

```

```

#only a temporal structure is included (AR1)

```

```

formula.st<- OBSERVED ~ 1 + f(ID.year1,DIFFR2,
model="ar1")+f(ID.area.year,model="iid") +f(ID.area,model="besag",graph="nc.adj") +
f(ID.year,model="rw1") + f(ID.area1,model="iid") +DIFFR2+ FEMALEHD +
PDENSITY + RESM + AGESTRUT + CRIME + INCARC + ECO + GN + BLACK

```

```

# Excute the model

```

```

model.inla.st <- inla(formula.st,family="poisson",data=data,E=EXPECTED,
control.predictor=list(compute=TRUE), control.compute=list(dic=TRUE,cpo=TRUE))
model.inla.st <- inla(formula.st,family="nbinomial",data=data,E=EXPECTED,
control.predictor=list(compute=TRUE), control.compute=list(dic=TRUE,cpo=TRUE))
model.inla.st <- inla(formula.st,family="zeroinflatedpoisson1",data=data,E=EXPECTED,
control.predictor=list(compute=TRUE), control.compute=list(dic=TRUE,cpo=TRUE))
model.inla.st <-
inla(formula.st,family="zeroinflatednbinomial1",data=data,E=EXPECTED,
control.predictor=list(compute=TRUE), control.compute=list(dic=TRUE,cpo=TRUE))

```

```

#Excute the models with linear combinations (the random slope models)

```

```

#Define Linear combination

```

```

lcs <- inla.make.lincombs(DIFFR2 = rep(1, 32),ID.year1= diag(32))
model.inla.st <- inla(formula.st,family="zeroinflatedpoisson1",data=data,E=EXPECTED,
control.predictor=list(compute=TRUE), control.compute=list(dic=TRUE,cpo=TRUE),
lincomb = lcs, control.inla = list(lincomb.derived.only = FALSE))
model.inla.st <- inla(formula.st,family="poisson",data=data,E=EXPECTED,
control.predictor=list(compute=TRUE), control.compute=list(dic=TRUE,cpo=TRUE),
lincomb = lcs, control.inla = list(lincomb.derived.only = FALSE))

```

```

# compute NLLK

```

```

cpo<-rep(NA,1536)
lgcpo<-rep(NA,1536)
for (i in 1:1536){
cpo[i]<-model.inla.st$cpo$cpo[i]
lgcpo[i]<-log(cpo[i])
}
NLLK<--sum(lgcpo[])

```

NLLK

```
#extract posterior estimated parameters
model.inla.st$summary.random$ID.year1
model.inla.st$marginals.lincomb
probs.above.zero <- as.numeric(lapply(model.inla.st$marginals.lincomb, function(X){ 1 -
inla.pmarginal(0, X) })))
```

```
#extract and plot the unstructured and structured spatial effect
re<-model.inla.st$summary.random$ID.area1[,2]
plot(density(re))
#structured spatial effect (CAR)
car<-model.inla.st$summary.random$ID.area[,2]
plot(density(car))
```

```
#extract structured spatial risk
CARmarginals <- model.inla.st$marginals.random$ID.area[1:48]
CARzeta <- lapply(CARmarginals,function(x)inla.emarginal(exp,x))
# exponentiate exceedence probability for structured spatial random effect
a=0
CARexceed1<-lapply(model.inla.st$marginals.random$ID.area[1:48],
function(X){ 1-inla.pmarginal(a,X) })
b=0.693 #log(2)
CARexceed2<-lapply(model.inla.st$marginals.random$ID.area[1:48],
function(X){ 1-inla.pmarginal(b,X) })
c=1.099 #log(3)
CARexceed3<-lapply(model.inla.st$marginals.random$ID.area[1:48],
function(X){ 1-inla.pmarginal(c,X) })
d=0.4055 #log(1.5)
CARexceed15<-lapply(model.inla.st$marginals.random$ID.area[1:48],
function(X){ 1-inla.pmarginal(d,X) })

carexc1<-as.numeric(CARexceed1)
carexc2<-as.numeric(CARexceed2)
carexc3<-as.numeric(CARexceed3)
carexc15<-as.numeric(CARexceed15)
```